DIGITAL MANUFACTURING ECOSYSTEM: THE EFFECTS OF DYNAMIC CAPABILITIES ON FIRM PERFORMANCE IN RESPONSE TO THE DIGITAL TRANSFORMATION OF THE MANUFACTURING SECTOR

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Ph.D Candidate: Marco Savastano

Tutor: Prof. Fabrizio D'Ascenzo **Co-Tutor**: Prof. Eusebio Scornavacca

Alla mia famiglia, che da sempre mi esorta a guardare più in là dell'orizzonte;

e a mia nonna Maria, cui ingegno e carattere mi danno la forza per affrontare al meglio le sfide che la vita mi offre.

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ABSTRACT

Fueled by platform technologies like mobile, social business, cloud computing, and big data analytics (BDA), as well as smart connected products and advanced robotics as part of cyber-physical systems, a new era is rising where technologies and business processes are so tightly linked to their customers and markets that the boundary between the internal operations of the enterprise and its external ecosystem is rapidly disappearing. Companies' digital strategy practically drives the roadmap and goals of many departments, from manufacturing, to sales, to HR and marketing. Business leaders are challenged to move their companies to the next level, that of digital business transformation, rapidly employing disruptive digital technologies such as IoT, robotics, and artificial intelligence to create new ways of operating and growing businesses (Puthiyamadam, 2017). The phenomenon of the Digital Transformation of the manufacturing sector (also known as "Industry 4.0" or "Smart Manufacturing") is finding a growing interest at both practitioner and academic levels, but it is still in its infancy and needs deeper investigation.

Indeed, even though actual and potential advantages of digital manufacturing are remarkable, only few companies have already made rapid advances by developing higher dynamic and digital capabilities necessary to achieve a superior performance in these settings.

The existing literature focused on the digital transformation of manufacturing is, on the one hand, dominated by consultancy reports and reviews of practitioners, which often lack the methodological depth and the predictive power of academic studies. Such publications contribute to the hype without offering adequate analytical substance. On the other hand, the majority of academic literature is characterized by technical publications, which, although highly valuable, focus on the engineering aspects of the technologies involved in this process and much less on the specific ways they are expected to disrupt the existing manufacturing and innovation practices, in terms of managerial strategies and process management. In order to address this gap, the present research aims to deeply understand the dynamic capabilities that companies need to develop in order to successfully implement the digital transformation and obtain a competitive advantage, in such a dynamic and fast-changing business environment characterized by digital disruption.

Therefore, the present study empirically investigates the factors that drive the development of digital manufacturing capabilities and the extent to which it affects organizational performance. A systematic analysis and review of the relevant literature in resource-based view, dynamic capability view and disruptive innovation theory (in the research domains of Innovation and Strategic Management and Information Systems) provided the basis for the development of the conceptual model that guided this research.

To achieve this ambitious goal, the research instrument was developed, construct domains were specified and an initial set of items was generated. This was followed by an extensive purification process which consisted of several expert review rounds, survey pre-tests and measurements refinement.

The study is based on an online survey, involving 110 manufacturing firms' executives operating in a wide range of industries. Using a Partial-Least-Squares (PLS) approach the data collected was used to test the model. The latter was successfully validated and statistically significant evidence was provided, revealing that high-order dynamic capabilities are directly and strongly associated with firm superior performance, and their effect is partially mediated by digital manufacturing capabilities developed by firms in fast changing and dynamic environments. Final results supported the conceptual research model and hypotheses of this research. These results are presented and discussed in detail in the following chapters of this thesis.

1. Chapter I: Introduction

The purpose of this chapter is to introduce the research topic and delineate the organization of this thesis. The first section outlines the factors that motivated this research by describing the phenomenon of interest. Main themes and research gaps in the relevant literature domains (i.e. Management and Information Systems) are then identified. Next, the goal of the research, the research question and the research objectives are described. The thesis outline is then presented before the chapter is concluded.

1.1 Digital Manufacturing Ecosystem

The rapid development and adoption of Internet and digital technologies dramatically changed business processes, leading to a disruptive digital transformation of the global industrial value chain (Li et al., 2009). In today's highly competitive environment, digital innovation is critical for addressing manufacturers' key business drivers and creating value. Advanced digital tools allow manufacturing companies to reduce costs, increase productivity, improve product development, achieve faster time-to-market, add value to products through dedicated services and enhance customer focus across various elements of the value chain (Brennan et al., 2015; Capgemini Consulting, 2012). Technological innovations have the potential, and some have already started, to change the traditional production methods for many products, with profound implications for how and where in the world they are manufactured.

The concept of *Industry 4.0* refers to a complex evolution of the entire industrial sector that includes technological advances in production equipment (i.e. Additive Manufacturing, new generation of robotics capable of sensing their environment), smart connected products and use of "internet of things" (IoT) in factories, cloud and mobile computing, artificial intelligence (AI), data tools and analytics, involving activities and stakeholders at all levels. These advances are changing how things are designed, produced and serviced around the globe, but also the strategic view involved in the management of businesses (Bogers, Hadar, & Bilberg, 2016; Magnani, 2017). In combination, they can create value by connecting different players and machines in a new "digital thread" across the value chain, relying on the availability of an unprecedented amount of data in order to address manufacturer's key business drivers (Lasi et al., 2014; Nanry et al., 2015). Companies and executives have, to some extent, improved at embracing digital transformation. CEOs recognize how much their digital strategy influences business goals, and CIOs (Chief Information Officers) are now completely involved in the strategic planning as well as regarded as some of the most integral members of the corporations' senior executives group (Puthiyamadam, 2017). Porter and Heppelmann (2015) described this overall trend as "*the most substantial change in the manufacturing firm since the Second Industrial Revolution*" (Porter & Heppelmann, 2015). With such a variety of developments influencing global manufacturing, a discussion of the likely future trajectories – including spatial, technological and operational – is both timely and necessary and involves both the innovation of production and management models (Brennan et al., 2015).

The "Digital Transformation" of manufacturing refers to a segment characterized by a remarkable market value, at least according to recent published reports. A research by Markets & Markets, an American B2B research firm, estimated a total value of $ 152.31 billion by 2022, with a compound annual growth rate (year-on-year percentage growth) of 14.72%. In Italy, according to data from a research by The European House Ambrosetti, this market accounted for 1.8 billion Euros in 2016 (Magnani, 2017).

As mass production has largely migrated to developing countries, European and US companies are forced to rapidly switch towards low volume production of more innovative, customised and sustainable products with high added value. To compete in this highly dynamic environment, manufacturers have sought new fabrication techniques to provide the necessary tools to support the need for increased flexibility and enable economic low volume production, along with the capabilities needed to exploit them in the most effective and efficient way (Mellor et al., 2014). Among them, for instance, *Digital Manufacturing* (DM) – sometimes referred to as Additive Manufacturing (AM) or 3-D printing - has been compared to such disruptive innovations as digital books, newspapers and music (MP3s) which enabled consumers to order their selections online as well as firms to profitably serve small market segments, configuring supply chains with no physical stores (i.e. e-business) and little or no unsold finished goods inventories. In this regard, some authors stated that digital manufacturing is beginning to do to manufacturing what the Internet has done to information-based goods and services (Denning, 2012). Indeed, it has long been hypothesized that implementing digital manufacturing in supply chains would lead to significant advantages, comparing DM to the Internet in its ability to cause a paradigm shift (Holmström & Partanen, 2014).

More in detail, Rayna & Striukova (2016) recently maintained that *disruptive technologies* are "*bearer of radical changes in business models and ecosystems*". Digital technologies, in particular, have led to major shifts in the industries that have adopted them. One of the key consequences of *digitization* has been to turn tangible objects into intangible ones. For this reason, digitization of products is also often referred to as a dematerialization (Rayna & Striukova, 2016). The dematerialization process - through which many products and services are entirely converted into bits in order to be transmitted over the Internet from the producer to the consumer - is followed by the re-materialization process of "real" digital products into physical goods (Berman, 2012). Moreover, Christensen (1997) in his work argued that disruptive technologies bring a very different value proposition than had been available previously in a certain market. These technologies initially might underperform established products in mainstream markets, but they have other features that a few fringe and new customers value, creating new markets. Products based on disruptive technologies are typically simpler, smarter, smaller, and frequently more convenient to use (Christensen, 1997). For instance, 3D printed products are representative of this category.

This fourth wave of technological advancement is supposed to realize the manufacturing of individual products in a batch size of one, while maintaining the economic conditions of mass production. Indeed, the core of the so-called "*factory of the future*" or "*smart factory*" is to combine the strengths of optimized industrial manufacturing processes with cutting-edge internet technologies (Blanchet et al., 2014; IEC, 2015). Hence it does not surprise that Industry 4.0 is currently experiencing an increasingly growing attention, especially in Europe.

Alongside to technological innovation, the organization structure together with required labor skills have undergone several major shifts and upgrades allowing factories to become more flexible and dynamic to face fast changing markets. It is not only a wave of disruptive technological innovation, but also a fundamental cultural change (Brettel et al., 2014; Lasi et al., 2014). Therefore, companies need to dynamically redesign their business models together with resources, processes and values, in order to achieve the important advantages disclosed by these new settings. It was argued that this process increasingly happen in the form of interfirm manufacturing networks ,enabled by integration across value chain activities (Brennan et al., 2015). Considering so, many fast-changing factors impacting the global manufacturing sector and its supply chains, many authors have emphasized the need for implementing high levels of flexibility, differentiating between “dynamic flexibility” and “structural flexibility” of supply networks. *Dynamic flexibility* is commonly achieved by continuously increasing the agility of the company’s factories, suppliers and its extended supply chains (Naylor et al., 1999; Goldman et al., 1995; van Hoek et al., 2001; Martin & Towill, 2000; Mason-Jones et al., 2000). *Structural flexibility* refers to the ease of re-configuring the company’s supply network in response to changes in demand, technology, local conditions, disruptions, and other factors in its operating environment (Christopher & Holweg, 2011). It also challenges the current norms regarding the way supply chains are configured and managed (Brennan et al., 2015).

When the effects of the environmental dynamism create a critical need to change in order to gain a competitive advantage – that is, enjoying greater success than current or potential competitors in its industry (M. A. Peteraf & Barney, 2003) - influential literature posits that firms need to build *dynamic capabilities* by developing new resources, reconfiguring existing ones, and combining them in order to obtain significant value by the contextual change (Drnevich & Kriauciunas, 2011; Helfat et al., 2007; Schilke, 2014; Winter, 2003; Zahra et al., 2006; Zollo & Winter, 2002).

The reminder of this research will deeply explore firms’ capacity of dynamically change their resource-base and capabilities in order to successfully respond to the disruptive change brought by the digital transformation of the fast-changing environment they operate in. The link between dynamic capabilities and firm performance will be empirically investigated, and the effect of the development of specific digital manufacturing capabilities evaluated.

1.2 Research Gap

Even though actual and potential advantages of digital manufacturing are remarkable, only a limited number of companies has already made rapid advances by developing higher dynamic and digital capabilities necessary to achieve a superior performance in these settings. According to Kiron et al. (2016) nearly 90% of digitally maturing organizations - companies in which digital technology has transformed processes, talent engagement, and business models -

are integrating their digital strategy with the company's overall strategy. Managers in these companies are much more likely to believe that they are adequately preparing for the industry disruptions they anticipate arising from digital trends. On the contrary, although almost all the respondents to a 2015 global survey of managers and executives conducted by MIT Sloan Management Review and Deloitte stated that their industries will be disrupted by digital trends to a great or moderate extent, only 44% evaluated their organizations as adequately prepared for the disruptions to come (Kiron et al., 2016). Moreover, PwC in their latest survey which polled 2,216 executives at companies with annual revenue of more than $500 million found that executives' confidence in their organization's digital abilities is actually at the lowest it has been since they started tracking it, a decade ago. Indeed, only 52 percent of these executives rated their Digital IQ, a scale of digital-driven change, as strong. This result is 15 percent lower than the year before. The investment in emerging technologies (as a percentage of total technology spending) grew just 1 percent over the 10-year period, with executives looking to digital initiatives primarily to increase revenue and reduce costs, showing that less priority is being placed on innovating and implementing the latest technologies into their products (Puthiyamadam, 2017).

At the same time, despite the increasing interest in this topic, scholarly inquiry on the economic and managerial effects of the digital transformation of manufacturing - in terms of firm's dynamic capabilities needed to take advantage of the fast changing environment, as well as its impact on business models and business model innovation - has transpired in the literature only recently, resulting in a limited understanding of this phenomenon (Cautela et al., 2014; Despeisse et al., 2016; Ford et al., 2016; Hahn et al., 2014; Rayna & Striukova, 2016; Schniederjans, 2017; Sommer, 2015). The existing literature focusing on digital manufacturing settings appears to suffer from a "double disease". First, it results dominated by consultancy reports and reviews of practitioners, which lack the methodological depth and the predictive power of serious research studies. Such publications contribute to the hype without offering much analytical substance. Second, the majority of academic literature is characterized by technical publications, which, although highly valuable, focus on the engineering aspects of the technologies involved in this process and much less on the specific ways they are expected to disrupt the existing manufacturing and innovation practices, in terms of managerial strategies (Hahn et al., 2014). All this suggests the need for more systematic studies focusing on the potential managerial opportunities associated with the emergence of a digital manufacturing ecosystem, in order to build up theoretical foundations in this area that results still largely in a nascent phase. Indeed, theory building in IS and Management fields is essential to provide important and valuable contributions to this research stream (Gregor, 2006). Based on the overview of the literature on digital manufacturing, the collective phenomena of disruptive innovation process and firm dynamic capabilities necessary to obtain a competitive advantage in such a turbulent environment is a research gap worth exploring.

In order to address this literature gap, the present research seeks to understand and verify how this digital manufacturing ecosystem impacts the resources of the businesses operating in this sector and what are the specific capabilities that companies need to develop to obtain a competitive advantage in such a dynamic environment characterized by disruptive innovation.

1.3 Research Goal

Digital manufacturing has been described as a disruptive innovation within a technologically dynamic environment (Berman, 2012; Birtchnell et al., 2016; Brennan et al., 2015; Denning, 2012; Hahn et al., 2014; Holmström et al., 2016; Jia et al., 2016; Kurfess & Cass, 2014; Petrick & Simpson, 2013; Rayna & Striukova, 2016; Wagner & Walton, 2016). Due to the resulting lack of extant theory in this area, to sustain this research effort this study will seek support in more consolidated bodies of knowledge, such as the Dynamic Capabilities View (DCV) and Resource Based View (RBV) – developed in strategic management domain and concerning the relationship between the concepts of firm capabilities and competitive advantage– as well as Disruptive Innovation Theory. It is a tradition of the IS discipline to take advantage of reference disciplines when investigating emerging topics (Benbasat & Weber, 1996; Zmud et al., 1989). This multidisciplinary approach aims to strengthen the potential contribution of this work to the research field. Indeed, by adopting the DCV, it is possible to define digital manufacturing as a capability that “may confer a competitive advantage by adding unique value to the firm through systematic change, particularly in industries characterized by rapid technological change" (Fainshmidt et al., 2016; Peteraf et al., 2013; Teece et al., 1997). Therefore, in order to deeply understand and being able to confirm the positive relationship between digital manufacturing and organizational performances, it is necessary to define - prior to testing - the relationship between digital manufacturing and firm dynamic capabilities.

Moreover, technology does not have intrinsic value (Teece, 2010): obtaining competitive advantage from it and transforming it into profits requires a business model based on the application of competencies and dynamic capabilities, and the ability to select and apply appropriate resources. In other words, obtaining a dynamic competitive advantage and turning it into a profitable venture requires competence (Prahalad & Hamel, 1990), the mastery of dynamic capabilities (Eisenhardt & Martin, 2000; Teece et al., 1997), and the ability to transform resources into value for the client (Cautela et al., 2014). Clearly, some *antecedents* exist that lead to the development of this dynamic capabilities and it is crucial to explore and analyse them in order to connect the phenomenon of interest to the abovementioned theories. Therefore, the main research question of this study emerges as follows:

> **RQ**: *What are the factors that drive the development of digital manufacturing capabilities (DMC) and to what extent does it affect organizational performance?*

Based on the abundant evidence from previous research, theory of Dynamic Capabilities proved that these capabilities contribute to performance by building new resources (i.e. "firm-specific assets" difficult or impossible to imitate) or problem-solving capabilities for the future, which may confer a sustainable competitive advantage (Sarkar et al., 2001; Teece, 2014).

In order to answer the main research question, the following research objectives were set:

- **RO1:** Develop a clear understanding of the *Digital Manufacturing Capabilities* (DMC);
- **RO2:** Explore what are the factors that drive the development of *Digital Manufacturing Capabilities*;
- **RO3:** Understand and assess the extent to which dynamic and digital manufacturing capabilities affect organizational performance.

To achieve these goals, in the next chapter this work will provide a systematic literature analysis to obtain a more clear overview of the existing literature on the phenomenon of interest, as well as an extensive literature review guided by the research question and objectives presented above, to rely on solid theoretical foundations.

The figure below shows a preliminary version of the conceptual model that will represent the structure of this research. It will be revised based on the evidences from the literature review, together with the development of associated hypotheses.

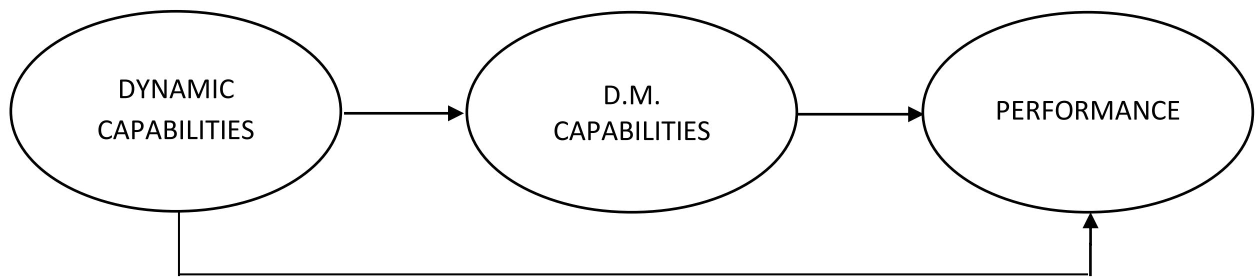


Fig. 1.1. Preliminary Conceptual Research Model

1.4 Research Strategy

The research strategy was developed aiming to achieve the research objectives and to answer the research question. A three-phase approach was developed:

Based on the results of some qualitative multiple case studies, carried out from the researcher as a preliminary exploratory stage, the first phase of the research is focused on the conceptualization of the research model. In this phase, the research question presented above serves as guidance to develop a detailed literature review, based on the results of a prior systematic literature analysis on the phenomenon of digital manufacturing. This phase explores the topics related to this study and highlights key concepts and theories emerging from the literature. This procedure provides substance for the development and refinement of the conceptual research model and associated hypotheses.

The second phase aims to develop the research instrument. In this stage, construct domains are specified and initial items generated. This is followed by an extensive refinement process which consists of several expert review rounds and survey pre-tests.

The third phase aims to test the theoretical model. To this purpose, a web-based survey with manufacturing firms' managers is carried out. This stage is then followed by the evaluation of the measurements and structural models. In the end, discussion, conclusions and insights for future research are provided.

1.5 Contributions

The key contributions of this research are several, as described in detail in the last chapter. First, through an extended systematic literature analysis and review, it shed light on the state of the art of the emerging literature concerning the digital transformation of manufacturing, in order to have a better understanding of the existing research in this area. This phase allowed the identification of fundamental theoretical concepts for the development of the conceptual research model.

Second, based on the Resource-Based View (RBV), Dynamic Capabilities View (DCV) and Disruptive Innovation theory, the conceptual model of this research introduces a completely new construct in the literature: the *digital manufacturing capabilities*. The latter was then operationalized through the development and validation of the research instrument (i.e. survey questionnaire). Thus, data resulting from the online survey based on this questionnaire allowed to test the predictive model.

Third, by testing the research model using a Partial-Least-Squares (PLS) approach, this study provided robust empirical evidence that not only digital manufacturing capabilities have a positive effect on firm performance, improving its competitive advantage over rivals, but they also partially mediate the positive direct effect of high-order dynamic capabilities on performance. Furthermore, even when including in the model several control variables considered in the literature to influence a firm's competitive advantage (e.g. market dynamism, firm size, firm age, use of technology, expenditure in innovation, etc.), the hypothesized partial mediation model resulted robust and was thus further supported.

These results contribute both to extend the literature in the research field of digital transformation and to provide manufacturing firms with important managerial insights.

1.6 Organization of the Remaining Chapters

This thesis consists of seven chapters. The thesis outline is summarised in Table 1.1

Chapter	Key Task(s)	Key Outcomes
1. Introduction	Introducing the research	Research goal, research question (RQ), research objectives (RO1, RO2, RO3) and preliminary conceptual research model
2. Literature Review	Systematic literature analysis and review of literature related to the research topics	Definition of reference theories and development of the conceptual research model
3. Conceptual Model and Research Hypotheses	Research design	Constructs definitions and updated research model (including research hypotheses: H1, H2, H3, H4)
4. Research Design and Methodology	Definition of Research paradigm and protocol	Updated research design and methodology
5. Research Instrument Development	Review of the literature for the development of the instrument scales and items	Research Instrument: web-based questionnaire both in English and Italian
6. Data Collection and Analysis	Data collection through the online survey and statistical analysis of the data gathered through statistical software (i.e. SPSS and SmartPLS)	Psychometric properties of the scales; Conceptual model testing (measurement model and structural model); presentation of the key results
7. Discussion and Conclusions	Discussion of consolidated findings from the previous research phases	Answer to RQ, research contributions, limitations and conclusions

Table1.1. Thesis Outline

2. Chapter II: Literature Review

2.1 Introduction

This chapter discusses the topics and themes that formed the foundations for this research. In this chapter the literature review is presented with the purpose of establishing the theoretical foundations of this research (Jasperson et al., 2002; Scornavacca, 2010; Webster & Watson, 2002). Given the multidisciplinary nature the phenomenon studied, it is important, at this stage, to define the informing disciplines that will structure the entire investigation (Benbasat & Weber, 1996).

To have a better understanding of the Digital Manufacturing Ecosystem (DME), it is firstly necessary to analyse the existing literature on this topic and further related subjects through a systematic literature analysis. Furthermore, since little is known about theories applicable to the digital transformation of manufacturing, it is then crucial to seek support in reference bodies of relevant literature and their respective correlated disciplines:

1) **Definition of Digital Manufacturing and Digital Ecosystems**
2) **Disruptive Innovation Theory, and the connected Resources-Processes-Values (RPV) theoretical framework**
3) **Firm's Capabilities and Manufacturing Capabilities**

Resource Based View (RBV) and Dynamic Capability View (DCV). Therefore, section 2.2 begins with a systematic analysis of the literature concerning the Digital Manufacturing Ecosystem. The goal of this initial segment is not to be exhaustive on this topic but to describe the existing literature in this field that is particularly relevant to have a clearer representation of the state of knowledge. Next, section 2.3 presents a comprehensive review of the literature through the aforementioned domains.

2.2 Literature Analysis

This section presents a detailed overview of the literature existing on the main topic of interest.

The *purpose* of this systematic analysis is to assess the current state of art of the academic literature regarding the digital manufacturing ecosystem phenomenon and find out patterns and eventual gaps to be addressed by the present and future studies. Thus, the literature analysis focuses on the digital transformation of production and, consequently, of the extended manufacturing value chain, brought by the wide development and adoption of digital technologies as well as the consequent alignment of firm's capabilities. In order to achieve this goal, the present study provides a systematic analysis of the extant body of literature on the aforementioned topic in the research domains of Management and Information Systems (IS) disciplines, to analyze and synthesize the development of this research stream as well as provide a representative picture of its current state. Insights and gaps resulting from this literature analysis will contribute to the development of a *research agenda* for the evolution of the state of knowledge in this scientific area (Schultze & Stabell, 2004).

The remainder of this section is structured as follows. The next sub-sections describe the methodology used to gather and analyze the data. Then, the results of the analysis are presented and discussed. The analysis concludes with a summary and recommendations for future research on the digital manufacturing phenomenon, providing an essential link to the subsequent literature review.

2.2.1 Methodology

A systematic literature analysis was selected as the research methodology for this phase. In the current work we follow the process and classification schemes described by Hoehle et al. (2012), taking also into account the structure described by Wareham et al. (2005) in their meta-analysis on electronic commerce and Yli-Huumo et al. (2016) in their systematic mapping study (Hoehle et al., 2012; Wareham et al., 2005; Yli-Huumo et al., 2016). The purpose of a systematic literature analysis is to provide an overview of a specific research area, to establish if research evidence exists and quantify the amount of evidence. Accordingly, there is an established tradition in social science research (i.e. Management and IS) of examining the existing research literature to better understand the "state of play" of research in the field, in order to to discern patterns in its development (Alavi & Carlson, 1992; Banker & Kauffman, 2004; Culnan & Swanson, 1986; Wareham et al., 2005). Following that tradition, the principal aim of this stage of the study is to understand the actual state of research on the digital manufacturing ecosystem phenomenon, by examining the relevant literature published to date in the Management and IS disciplines. According to these research traditions, the subsequent steps were followed:

- **Identifying, reviewing and analyzing the existing literature** on the development of a Digital Manufacturing Ecosystem through the adoption and utilization of digital and mobile tools or platforms in the *manufacturing industry*;
- **Identifying theoretical and methodological approaches** generally used to investigate the digital transformation of the extended manufacturing value chain through the adoption and utilization of such applications and tools;
- **Identifying research areas and possible gaps** within the existing literature concerning the adoption and impact of digital and mobile tools leading to a paradigm shift of the manufacturing industry, in order to redact a complete *research agenda* useful for further scientific contributions.

2.2.1.1 Definition of Research Questions

As the first stage of the systematic literature analysis, the research questions have been defined consistently with the research purpose. Thus, the **primary research question** that guides the present literature analysis is as follows:

- ***What is the "state of art" of the academic literature regarding the Digital Manufacturing Ecosystem phenomenon?***

In order to fulfil the analysis of the research literature and answer to the main research question, the following **sub-questions** were posed:

- **Which enabling manufacturing digital technologies have been studied?**
- **What is the main focus/topic of the studies?**
- **What are the main domains identified in the current research?**
- **What Industrial sectors and actors (i.e. large companies, SMEs, consumers, etc.) are involved in this research field?**

- **What was the research method used?**
- **What was the research approach (qualitative, quantitative; empirical, conceptual)?**
- **What was the main contribution of the paper analyzed?**
- **What regional context was the research undertaken?**
- **What are the current gaps in this research field?**

Past literature analyses and review studies demonstrated that these type of questions unable researchers to successfully synthesize research fields and identify trends, gaps, weaknesses and possible research paths that will guide future investigations of the phenomenon studied (Alavi & Carlson, 1992; Hoehle et al., 2012; Scornavacca et al., 2006).

The following sections of the paper will provide evidences and insights from the analyzed literature in order to answer to each one of the questions outlined above.

2.2.2 Research Process

In order to conduct the present literature analysis in a systematic way, a predetermined phase sequence was followed. Fig 2.1 illustrates the sequential research process steps and outcomes.

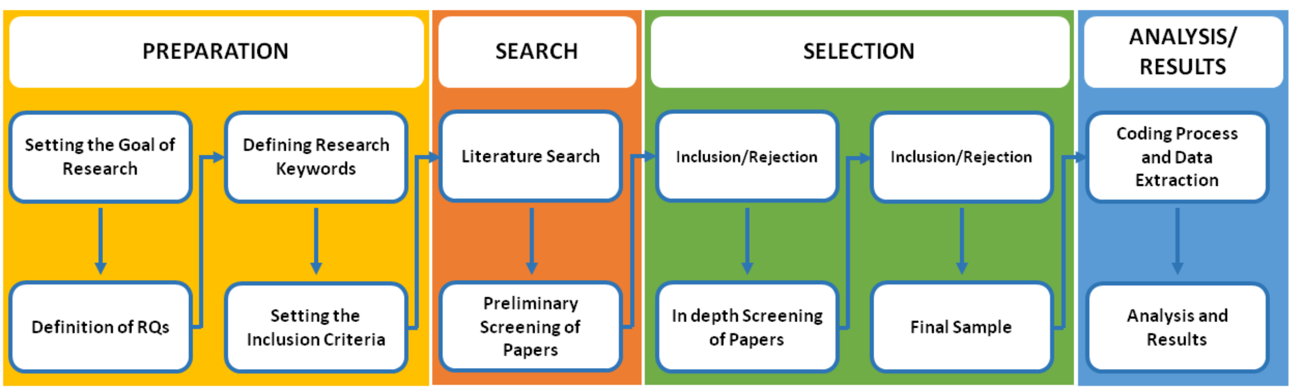


Fig. 2.1. Research Process Flow

As a subsequent stage after the definition of the RQs, it was necessary to set the search protocol to find all the relevant scientific papers on the research topic. Pre-defining the methods and criteria that will be used to undertake a systematic literature search is crucial to reduce the possibility of researcher bias. The primary parameters to carry out our literature source are as follows:

- **Keywords/search terms:** the keywords chosen for the literature search were *Digital Manufacturing*, *Industry 4.0* and *Additive Manufacturing*, which are the most common, inclusive and representative terms in the literature associated with the phenomenon we are investigating. A comprehensive definition of each one of these terms is provided in the literature review section (see paragraph n. 2.3.1.1).
- **Research fields and sources:** coherently with the research aim, only Management and IS fields sources were selected (databases and top journals in these research fields, such as ProQuest, ABI/Inform, Science Direct, Emerald Insight, etc.). Therefore, we carefully filtered our search for excluding all the articles not related to these two main paradigms. Many results, indeed, were found to concern exclusively technical aspects of the phenomenon of interest and were related to mechanical engineering, architecture, computer science, material science and biotechnology fields. The literature search was conducted through comprehensive bibliographic databases in order to cover a broad range of top journals. The sources explored are shown in Table 2.1.
- **Relevant research:** given the tremendous breadth of research on this topic, referring to a high number of disparate disciplines, we decided to select only *Peer reviewed/Scholarly journal articles*, excluding conference proceedings, professional journals, industry reports and specialized publications on magazines. This strategy circumvented also book reviews, editorials and opinion statements as well as similar "non-scholarly" work. This choice is motivated by the requirement of seeking only high quality publications from top rated journals. The full list and frequencies of the journals included in this study is available in Table 2.3.
- **Time period:** the last 20 years. Even though the concept of digital manufacturing was originated by the use of rapid prototyping and computer aided design and manufacturing (CAD/CAM Technologies), which have been adopted in the production process more than twenty years ago, here we are focusing on broader applications, extended to the production of end-products, which became a research topic more recently. Indeed the oldest paper in our sample is from 2001.
- **Language:** English

Online Research Platform	**Databases**
EBSCOhost	Academic Search Complete; Business Source Premier; Ebsco Discovery Service (EDS); etc.
ProQuest	ABI/INFORM Global; Emerald Insight, etc.
Science Direct	Elsevier e-journals and e-books

Table 2.1. Selected Online Databases for the Literature Search

2.2.3 Sample

After designing the research protocol and choosing the abovementioned electronic databases, we conducted the literature search. From the keyword search, limited to peer-reviewed scholarly journal publications, we carried out the first selection by excluding papers with subjects and titles that did not fulfill our research protocol (for instance: Advanced Engineering Informatics, Civil Engineering, Medical and Biological Engineering and Computing, Computer Standards & Interfaces, Biotechnology, etc.). To do so, we refined the results using the advanced search tools offered by the databases. After this first selection resulted a total of 739 articles.

The next stage was the **screening of papers**. To this purpose we examined title and abstract of every paper selected in the previous phase. Thus, we exported the results of our literature search in a citation management software (i.e. Mendeley) and carefully analyzed these two elements together with the keywords chosen by the author/s and the journal. Any article considered pertinent to the research topic was selected for further analysis. The general guideline for article selection was the following:

- The **central theme** should be digital transformation of manufacturing and applications related to the definition/development of a Digital Manufacturing Ecosystem;
- Papers should focus on the **managerial and market implications** of this phenomenon (both from demand and supply viewpoints).

Following these criteria, we excluded all those papers not relevant to our purpose and clearly out of the scope of this study. As an additional exclusion criterion, we decided to ignore papers less than three pages in length. Furthermore, we compared the articles resulting from the three different keywords as well as databases, and found out the duplicates to be excluded. In total there were 40 articles resulting more than once through the different keyword sources and databases. Putting the articles together, without duplicates, the final amount was of 139 publications (see Tab. 2.2). Those papers were included in the next screening phase.

KEYWORD	**SOURCE**	**TIME PERIOD**	**CATEGORIES EXCLUDED** (Some examples of excluded subjects)	**RESULTS (N)**
1. Digital Manufacturing	ProQuest/ EBSCOhost	1986-2017	algorithms; cooling; genetic algorithms; mechanical properties; neural networks; semiconductors	203
	Science Direct			12
2. industry 4.0	ProQuest/ EBSCOhost	1986-2017	agricultural policy; agricultural production; agriculture; baby boomers; cardiovascular disease	80
	Science Direct			6
3. Additive Manufacturing	ProQuest/ EBSCOhost	1986-2017	Alloys; aluminium; bioengineering; bond strength; ceramics; composite materials; cooling; corrosion resistance; design engineering; engineers; grain size; issue engineering; laser sintering; lasers; materials research; mechanical engineering; mechanical properties; medical equipment; metals; numerical controls; particle size; polymers; powder metallurgy; sintering; stainless steel; temperature; titanium alloys	63
	Science Direct			21
			TOT All Databases	179
			TOT Duplicates	-40
			FINAL TOTAL	**139**

Table 2.2. Selected Publications

2.2.4 Analysis and Coding

Next stage consisted in reading entirely all the selected papers with a twofold objective:

1. Ensure that all the selected publications were consistent with the selection criteria;
2. Recognize and analyze the patterns contained within the paper through a **coding process**.

From this in depth selection, we found 23 articles not responding to our search protocol and inclusion criteria for different reasons (i.e. research domain, scope, main focus, contribution). After their exclusion, the final sample was composed of **116 primary papers,** selected for detailed analysis**.**

Table 2.3 on page 31-32 shows the selected articles listed by journal and year of publication. The starting date of the literature search was 2000 since, from a prior pilot search we carried out, we found out that literature in this area is relatively recent and no relevant publications were retrieved before that date in accordance to our research protocol. In addition, it is noteworthy that 74% of our sample was published in the time frame 2014-2016. To this purpose, the chart below (Fig. 2.2) shows the distribution of articles based on the publication year. It is easy to observe how the majority of them is concentrated in this 3-year period, registering a high growth of contributions in this research area. As for the year 2017, the number of publications results very low since our literature search was carried out between December 2016 and January 2017.

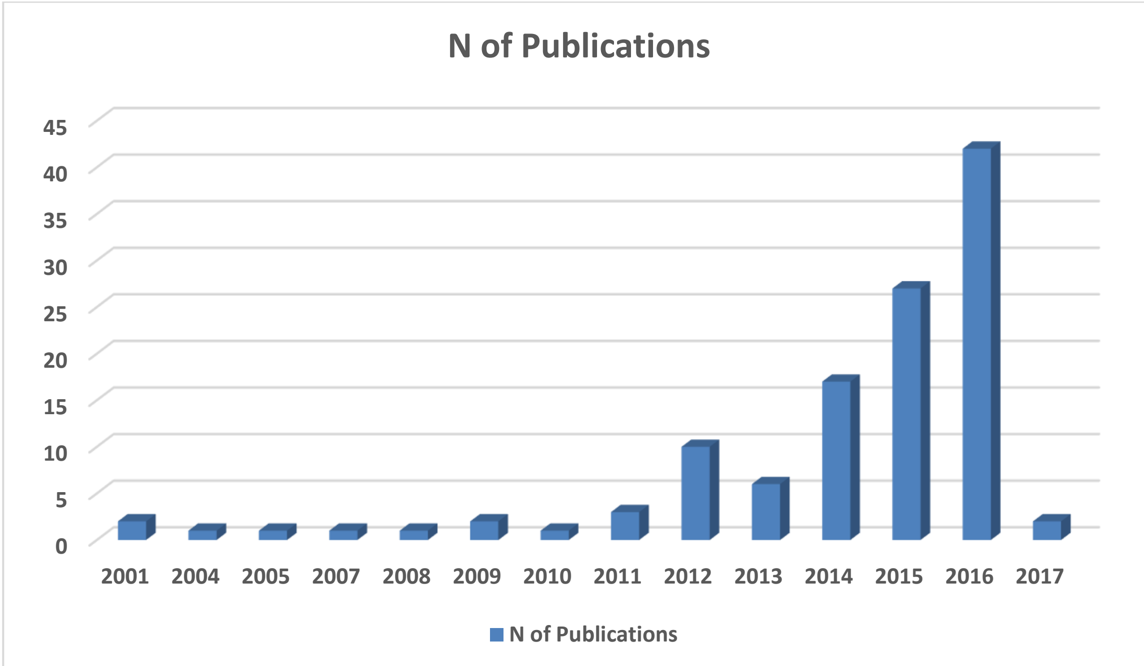


Fig. 2.2. Articles by Year of Publications

Moreover, Table 2.3b shows the distribution of publications ordered by keyword used in the keyword search. Terms listed with a slash - for instance DM/AM or Industry 4.0/AM - indicate that the same publication resulted from the keyword search of both terms. It is interesting to note that the term Additive Manufacturing (AM) has obtained the highest absolute score in terms of publications (40% of the total) in comparison to Digital Manufacturing (DM, 22%) and Industry 4.0 (15%). However, it must be emphasized that the latter term was coined and has spread very recently (around 2013).

Keywords	**2001**	**2004**	**2005**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**Total**	**%**
AM	1		1					1	1	4	8	8	20	2	46	40%
DM	1	1		1	1	2		2	7		1	1	7		24	21%
DM/AM							1		2	2	5	9	6		25	22%
Industry 4.0											2	7	8		17	15%
Industry 4.0/AM											1	1	1		3	3%
Industry 4.0/DM												1			1	1%
Total	2	1	1	1	1	2	1	3	10	6	**17**	**27**	**42**	2	**116**	
%	2%	1%	1%	1%	1%	2%	1%	3%	9%	5%	15%	23%	36%	2%		

Table 2.3b. Search Keywords results by year of publication

In light of this, it is possible to observe that publications related to the term "Industry 4.0" have quickly grown from 0 to a maximum of 8 per year in the period 2013-2016, exceeding even the value of DM in the same years. These dynamics can be more clearly visualized on Figure 2.3.

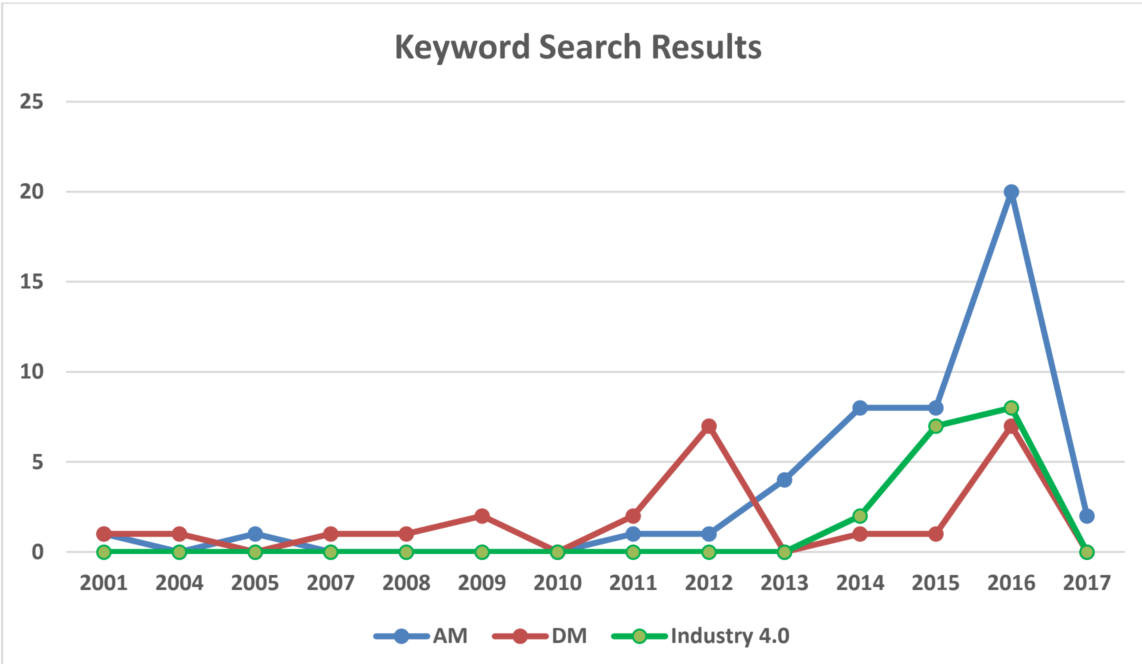


Fig. 2.3. Publication by Single Keyword Search

2.2.4.1 Coding Process

The first step undertaken for the data analysis involved a coding procedure. We followed coding techniques outlined by Alavi and Carlson (1992) as reported in Hoehle et al. (2012), investigating all the identified articles in order to address the above mentioned research questions (Alavi & Carlson, 1992; Hoehle et al., 2012). A data matrix was designed to collect the information needed, visualized in the form of codes, as well as highlight similarities and differences between the various research articles. Next, as mentioned all the 116 papers were entirely read and reviewed for the association of coding patterns. In a few cases where the paper resulted not univocally codifiable, an expert faculty was asked to codify in turn the paper until a consensus between the two reviewers was achieved. The coding process gathered basic information of the papers, including for instance the name(s) of the author(s), year of publication, the country based on the author’s affiliation (based on the first author's affiliation when different), as well as more in depth information such as main focus, method and major findings of each paper. After reading them, we also updated the categories of the data matrix or created new ones when the papers revealed something new. The extracted data items were collected to Excel, which helped us to organize and analyze them. Also R software was used during this process to run some specific analysis. First, raw codes were created in order to collect and record all the different facets present within the papers. Subsequently, these codes were clustered in macro categories to have a clearer understanding of the state of literature. Table 2.4 exemplifies the coding procedure by outlining the codes chosen for the research article taken as an example.

Codes	*Publication*
Technology/Process Type	3D Printing
Country/Regional Context	USA
Focus/Main Topic	Business Model Innovation
Domain/Research Field	Technology and Innovation Management
Sector/Industry/Firm Size	Manufacturing
Research Design	Literature Survey
Research Approach	Qualitative
Source of Data	Secondary
Key Contribution	Insights

Table 2.4. Example of Data Items for the Coding Process

JOURNAL	'01	'04	'05	'07	'08	'09	'10	'11	'12	'13	'14	'15	'16	'17	Total	%
A I B Insights												1			1	1%
African Journal of Business Management											1				1	1%
Business & Information Systems Engineering										1	3	1			5	4%
Business Horizons									1			2			3	3%
Business Process Management Journal													1		1	1%
Clean Technologies and Environmental Policy												1			1	1%
Computer Networks													1		1	1%
Computers in Industry		1				1					1	1	4	1	9	**8%**
Creativity and Innovation Management												1			1	1%
European Journal of Operational Research													1		1	1%
European Networks Law and Regulation Quarterly (ENLR)												1			1	1%
Foundations of Management													1		1	1%
Industrial Management & Data Systems													2		2	2%
Info											1				1	1%
Intereconomics												1			1	1%
International Entrepreneurship and Management Journal											1				1	1%
International Journal of Management & Information Systems (Online)											1				1	1%
International Journal of Operations & Production Management												2			2	2%
International Journal of Physical Distribution & Logistics Management													2		2	2%
International Journal of Production Economics											1	1		1	3	3%
International Journal of Production Research						1							3		4	3%
IUP Journal of Operations Management													1		1	1%
Journal of Centrum Cathedra												1			1	1%
Journal of Engineering and Technology Management												1			1	1%
Journal of Humanitarian Logistics and Supply Chain Management												1			1	1%
Journal of Industrial Engineering and Management												1			1	1%
Journal of Information Systems & Operations Management										1					1	1%
Journal of Intelligent Manufacturing					1			2							3	3%
Journal of International Business Studies													1		1	1%

JOURNAL	**‘01**	**‘04**	**‘05**	**‘07**	**‘08**	**‘09**	**‘10**	**‘11**	**‘12**	**‘13**	**‘14**	**‘15**	**‘16**	**‘17**	**Total**	**%**
Journal of Manufacturing Technology Management				1					1		2	1	4		9	**8%**
Journal of Manufacturing Technology Research										1					1	1%
Journal of Marketing Theory and Practice													1		1	1%
Knowledge Horizons - Economics													1		1	1%
MIT Sloan Management Review									1	1			1		3	3%
Mobile Networks and Applications													1		1	1%
Nexus Network Journal									2						2	2%
Northwestern Journal of Technology and Intellectual Property													1		1	1%
Operations Management Research													1		1	1%
Procedia - Social and Behavioral Sciences													1		1	1%
Procedia Manufacturing												2	1		3	3%
Proceedings in Manufacturing Systems												1			1	1%
Production Planning & Control											1		1		2	2%
Rapid Prototyping Journal	2		1				1	1	1		1	2	1		10	**9%**
Research Technology Management										1	1	4			6	**5%**
Strategy & Leadership									1						1	1%
Studia Commercialia Bratislavensia										1					1	1%
Supply Chain Management											1				1	1%
Symphonya									1						1	1%
Technological Forecasting and Social Change									1		1		9		11	**9%**
Technology Innovation Management Review											1	1			2	2%
Technovation													1		1	1%
Telecommunications Policy												1			1	1%
The Journal of Business Strategy									1						1	1%
Total	2	1	1	1	1	2	1	3	10	6	17	27	42	2	**116**	100%
%	2%	1%	1%	1%	1%	2%	1%	3%	9%	5%	**15%**	**23%**	**36%**	2%	100%	

Table 2.3. Selected Articles Listed by Journal and Year of Publication

2.2.5 Findings

2.2.5.1 Technologies

Given the breadth of our sample and the different keywords used for the literature search, the classification of the technologies encountered in the literature gave several diverse results.

Table 5 reports the five macro categories created to label the nature of the technologies described in the papers. To do so we referred to the definition given by authors and to the technology standards (e.g. ASTM International). However, these categories are so broad that such categorization conveys limited information. As a consequence, we added a description as well as the single specific codes to further qualify these high level categories.

Clustered Codes	Description	F	%
AM Technologies	**Different technologies referable to Additive Manufacturing:** 3D Printing, 3DP, 3DP/AM, 3DP/DDM, AM, AM (Digital Fabrication), AM/3DP, AM/RP, Consumer 3DP, Home fabrication, DDM, Digital Fabrication, Digital Fabrication (DF), Digital Manufacturing Technologies, DM, Rapid Manufacturing, Rapid Manufacturing (RM), RP, 3DP	68	58.6%
Advanced Manufacturing Systems (Industry 4.0/IoT)	**Technological tools and advanced systems employed in the Manufacturing Sector, often related to the Industry 4.0 framework and IoT concept:** Robotic Process Automation, Advanced Manufacturing Technologies (AMTs), Advanced Materials Technologies, Advanced Production Systems (CPPS), Advanced systems of additive technologies, Cloud-integrated Cyber-Physical Systems (CCPS), Cyber-Physical Manufacturing Systems (CPMSs), Smart Factories, Cyber-Physical Systems (CPS), Smart Factories, Digital systems, Open-source collaboration platform, smart sensors, digital enterprises, Smart Factories, Industry 4.0, IoT, Smart Factories/Industry 4.0, Online 3DP Platforms, Smart Factories/Industry 4.0, Web-based RP & Manufacturing systems	25	21.6%
ICT	**Information and communication technologies for the DME:** 3D sensors, AR and Web technologies; Big Data Analytics; Cloud computing; Digital Technologies; Digitally driven technologies (ICT); ICT; Industry 4.0 enabling technologies (ICT); Information Systems	16	13.8%
Digital Design Tools	**Digital tools employed in the design phase of products and spare parts:** CAD/CAM tools; Digital Design Tools/RP; Prototyping Technologies	3	2.6%
Innovation Process	**Focus on the innovation process:** manufacturing process innovation; Innovation; Technological Innovation Activities	4	3.4%
TOT		116	100%

Table 2.5. Technology Categories

Looking at their distribution, it is possible to identify that over half of the sample (58.6%) was focused on *Additive Manufacturing* technologies, differently identified as 3D Printing (e.g. Adams & Downey, 2016; Berman, 2012; Birtchnell et al., 2016; Jia et al., 2016; Park et al., 2016; etc.), DDM, Digital or Home Fabrication (e.g. Buxmann & Hinz, 2013; Steenhuis & Pretorius, 2016; etc.) and Rapid Manufacturing technologies (e.g. Atzeni et al., 2010; Hopkinson & Dickens, 2001; etc.). All these technologies can be included in the additive manufacturing category. Digital and home fabrication are often associated to studies focused on the user-producer perspective (also known as "Prosumer") and related to consumer products/services sector.

Secondly, 25 publications (21.6% of the sample) were found to be focused on digital technological tools developed and applied for the creation of *Advanced Manufacturing Systems*. For instance, Cyber-Physical

Manufacturing Systems (CPMSs), Smart Factories, Open-source collaboration platforms, 3DP Platforms and Web-based Rapid Prototyping & Manufacturing systems are the basic elements of the Industry 4.0 framework. (e.g. Dean et al., 2009; Denning, 2012; Francalanza et al., 2017; Ivanov et al., 2016; Lasi et al., 2014; Rennung et al., 2016).

The third category includes *information and communication technologies* (ICT) fundamental for the creation of a digital-enhanced ecosystem, such as Information Systems, Smart Sensors and Products, Web technologies, Cloud Computing and Big Data Analytics (e.g. Brenner et al., 2014; Candel Haug et al., 2016; Weichhart et al., 2016; etc.).

The last two categories include *Digital Design Tools,* such as Rapid Prototyping and CAD/CAM tools (Canciglieri et al., 2015; Marion et al., 2012; Siller et al., 2008), and papers focused only on the *Innovation process*/activities (Featherston et al., 2016; Filieri & Alguezaui, 2012; Milewski et al., 2015; Veugelers, et al., 2015).

2.2.5.2 Main Focus

Next step was to identify the main focus of the primary papers. Thus, each article was classified primarily according to the definitions given by the authors. The codes were than grouped in macro-themes to facilitate the analysis of the results.

From the coding process resulted thirteen main categories of different topics. Table 2.6 shows that the categories resulted highly fragmented. Taking into account their frequency values, it is possible to highlight that only three of them have a value greater than 10%:

- <u>*Manufacturing Supply Chain Reconfiguration*</u> *(35.3%):* this category concerns papers focused on the radical paradigm-shifts occurring in the manufacturing settings and operations configuration due to innovative technologies development and adoption (e.g. the evolution of manufacturing through mass production, mass customization and 3DP/digital manufacturing processes, CPPS and Smart Digital factories characterizing Industry 4.0). This technological paradigm-shift comes in response to the need of reducing costs, lead times and time to market of standard manufacturing processes while at the same time making the system adaptable to the changing needs of the customers (Dean et al., 2009).

  The impact of technology has been investigated both at firm level, in terms of shifts in value propositions and creation of additional value streams (Rylands et al., 2016), as well as on global manufacturing industry processes and competitive dynamics (Weller et al., 2015).

  In more detail, some studies have analyzed the extent to which disruptive digital manufacturing technologies are driving structural shifts in supply chain management and configurations by revolutionizing the production process as well as rethinking many traditional operations management practices (i.e. inventory management, job shop scheduling, and batch sizing) and leading to value-added achievement through distributed manufacturing strategies (Holmström et al., 2016; Holmström & Partanen, 2014; Khajavi et al., 2014; Liu et al., 2014). For instance, Laplume et al. (2016) in their explorative study investigated the potential implications of open-source AM and 3D printing technologies for the configuration of new global value chains (GVCs) or the modification of existing ones. The study suggests that diffusion of 3D printing technologies in an industry is associated with a development toward shorter and more dispersed global value chains. Therefore, in some industries the new manufacturing technology is likely to pull manufacturing value chains in the direction of becoming more local and closer to the end-users (Laplume et al., 2016).

The abovementioned studies mainly present either insights or propositions and conceptual frameworks/scenarios that may serve as a starting point for further research, as well as fewer in number conceptual models to be tested (see Table 2.15 on page 45). The impact of this new ecosystem on personalized products market, meaning the potential of digital manufacturing to increase the level to which customers are virtually integrated in a manufacturer's supply chain (Oettmeier & Hofmann, 2016) and the modification of the value chain activities, received very limited investigation in existing researches (Chiu & Lin, 2016).

A further stream of research included in this category investigates the phenomenon of ***Digitally-enabled Collaborative Manufacturing Networks,*** indicating industrial networked structures where collaboration among different players comes through the intense cooperation and knowledge sharing between loosely connected entities (i.e. large companies and SMEs, users, consumers), improving innovation processes and creating value. For instance, Beckmann et al. (2016) in their paper studied the digitization of design and manufacturing through a web platform (DMC platform - Digital Manufacturing Commons) which supports the democratization of design and manufacturing model development and has the ability to bring together SMEs, large enterprises, software vendors, researchers, and intermediaries into an ecosystem in which participation is mutually beneficial, in order to promote the manufacturing competitiveness of SMEs. These collaborative networks and platforms represent the foundations of Industry 4.0 for regardless of firm size.

Finally, another important topic is connected to the multiplication of channels interested by the AM technologies. The implementation of ***e-commerce channels*** to transfer design files for Additive Manufacturing implications for the supply chain management and the business value chain activities (Eyers & Potter, 2015). Although this topic seems at the basis of the present research field, it didn't receive much attention in the existing research.

- <u>*Democratization of Manufacturing*</u> *(14.7%):* also this category includes different research streams and topics. It describes radical changes in the entire value chain around how products are designed, funded, sourced, manufactured, and distributed (Hoover & Lee, 2015). Digital manufacturing and home fabrication revolutions are expected to produce a substantial contribution toward the democratization and disintermediation of invention, economy, market and society (enabling more people not only to receive but also to conceive new knowledge). 3D printing has the potential to bring personal digital fabrication to everyone and to boost the creation of new products and businesses, thanks to the open source innovation and the emergence of collaborative design among communities of connected users, turning consumers into creators and, as a result, into competitors of incumbent companies.

  Some studies were focused on ***Makers and FabLab Movements***, seeking how digital fabrication technologies combined with new services (through fab-spaces, that is fabrication spaces) can help transfer familiar principles from the digital to the physical world, by empowering user-entrepreneurs to turn their ideas into real prototypes or products in order to start a business in a comparatively easy way (Anderson, 2012; Buxmann & Hinz, 2013). Mortara and Parisot (2016), in their work map the current Fab-spaces landscape and provide a detailed hierarchical classification of these emerging organizations by taking the particular perspective of those who use the Fab-spaces for launching their entrepreneurial ventures (Mortara & Parisot, 2016). From this settings emerges the research investigating the concept of **Prosumer**. It refers to the important social change of individuals being directly involved in the design and production of the goods that they consume. Innovations enable end-users to have authority over the design and production of their own original one-off goods, reshaping the traditional role of passive consumers in the production process by providing them with the highest level of involvement (Fox & Li, 2012; Rayna et al, 2015; Yoo et al., 2016).

  Another stream representing a sub-level of this category is the research concerning ***Peer-to Peer exchanges.*** It is focused on trading or exchanging of 3D designs/models over the web, similar to the sharing of music and movie files in online peer-to-peer exchanges (Burns & Howison, 2001).

  The category of *Democratization of Manufacturing* is strictly connected to the topics covered by the *Digital Transformation of Products/Services category* (5.2%), but while the latter adopts a business strategy perspective, the present one is focused on the user/consumer perspective.

- <u>*AM Features/Applications*</u> *(10.3%):* This category presents publications concerning the state of art, evolution and trends of Additive Manufacturing and 3D Printing Technologies. Technological characteristics, phases of the production process as well as main advantages and disadvantages of

AM applications in comparison to conventional techniques in terms of efficiency, times and costs are presented (Berman, 2012; Pîrjan & Petrosanu, 2013). Recent applications in different industries are taken into account and possible future scenarios are outlined, in order to assess disruptions and consequences the technology might cause to firms and consumers (Kietzmann et al., 2015). Data from our sample show that this category of publication is quite well covered, and provides mainly insights (see Table 2.16) based on research commentary studies (10 papers over 12, the 83%).

Research on <u>*Business Model Innovation*</u> was found in only 9 papers (7.8% of the sample). Publications in this category are focused on how digital manufacturing technologies imply to modify business model components, allowing companies to create and capture value as well as satisfy customers' needs. The low amount of publications is further confirmed by the limited attention received by the connected category of *Impact on Value Proposition* (1.7%). Bogers et al. (2016) explored how AM technologies may influence the viable business models within the consumer goods manufacturing industry, with the aim to answer the question of how emerging AM technologies impact business model development and operations in this context (Bogers et al., 2016).

Business model innovation is not just about implementing more and better technologies. It involves also *digital congruence*, the process of aligning company's culture, people, structure, and tasks. Indeed, history has shown that technological revolution without adequate business model evolution is a pitfall for many businesses (Rayna & Striukova, 2016).

The subsequent four categories listed in table 7 (*Economic/Competitive Impact of Digital Transformation; Technology Assessment and Comparison; Technological Development Dynamics and Digital Transformation of Products/Services*) present a similar frequency value in terms of number of publications, which results low probably due to the strong connections to the three main categories presented above. In addition, while for "Economic/Competitive Impact of Digital Transformation" the level of analysis is the entire industry or country, for "*Digital Transformation of Products/Services"* the focus is on firms and their customers.

Focus (Clustered Codes)	Characterization	Codes	%
Multiple	Intellectual Property Law and Democratization of Manufacturing	1	0.9%
Impact on Value Proposition	Customer Satisfaction; Impact of Disruptive Technology on Value Proposition	2	1.7%
Intellectual Property Law	Anti-Piracy Strategies; Intellectual Property Protection	2	1.7%
Sustainability	Humanitarian 3DP; Sustainable Product Design, Development and Manufacturing	3	2.6%
Digital Knowledge Dissemination	AM Users Education and Engagement; Digital Knowledge creation/dissemination and Value Creation	4	3.4%
Digital Transformation of Products/Services	Dematerialization due to Increased Digital Consumption; Digital Service Management; Digitalized Product-service systems (PSS); Digitally Enhanced New product development (NPD); Smart-Connected Products	6	5.2%
Technological Development Dynamics	Contribution of Standards to innovation; Enterprise 3D Printing Adoption; Technological Development Alignment; Technological Forecasting and Fiction; Technological Process Innovation	6	5.2%
Technology Assessment and Comparison	Cost-Benefit Analysis/Estimation; Technology Assessment and Evolution	6	5.2%
Economic/Competitive Impact of Digital Transformation	Backshoring of Value Chain activities; Digital Competitiveness; Economic impact of AM; Macro-Economic Impact of Community Innovation; Reindustrialization; Technological discontinuity and New Ecosystems	7	6.0%
Business Model Innovation	Business Model Innovation; Digital Transformation of Companies	9	7.8%
AM Features/Applications	AM/3DP Features and Applications; AM/DM Implementation;	12	10.3%
Democratization of Manufacturing	Democratization and Disintermediation of Manufacturing; Open-source Innovation; Makers and FabLab Movements; Peer-to Peer Exchanges; Prosumption; Technology-User/Consumer Interaction; Users' Technology Acceptance; Value co-creation and Social Innovation	17	14.7%
Manufacturing Supply Chain Reconfiguration	Digitally-Enabled Collaborative Manufacturing Networks; Digitally-Enabled Project Manufacturing; E-commerce channels for AM; Reconfiguration of Manufacturing (Advanced Manufacturing); Supply Chain Planning Optimization Models; Value Chain/Supply Chain Reconfiguration	41	35.3%
TOTAL		**116**	**100%**

Table 2.6. Main Focus of the Papers Ordered by Frequency

2.2.5.3 Research Domain

As per the previous Focus category, there are few domains that are clearly dominant in our sample. Indeed, a broad look at the top level codes indicates a concentration of the research principally in four main categories: Supply Chain Management/Operations Management; Technology and Innovation Management; research that interests multiple domains, and Production Economics. Among the "Multiple" category are included academic disciplines such as Strategic Management; Decision Making, Marketing and Manufacturing Research. *Production Economics* concerns the design and development of advanced manufacturing information systems and platforms as well as studies focused on the growing phenomenon of Industry 4.0. Table 2.7 represents the distribution of the different domains within the analyzed sample.

Category	N	%
Circular Economy	1	0.9%
International Business Research	1	0.9%
Multichannel Management	1	0.9%
Product/Service Innovation	1	0.9%
Manufacturing Economics	2	1.7%
Organization Science	2	1.7%
Consumer Research	3	2.6%
Industrial Economics	3	2.6%
Strategic Management	3	2.6%
Decision Making (for Innovation)	4	3.4%
Entrepreneurship and Business Research	4	3.4%
IP Law	4	3.4%
Service Science	4	3.4%
Sharing Economy	4	3.4%
Education	5	4.3%
MIS	6	5.2%
Innovation (Process)	9	7.8%
Production Economics	11	9.5%
Multiple	15	12.9%
Technology and Innovation Management	16	13.8%
SCM/OM	17	14.7%
Total	**116**	100%

Table 2.7. Domain Codes

As a confirmation of the evidences from the "*focus*" categories, domains as *Entrepreneurship and Business Research* (3.4%) and *Strategic Management* (2.6%) received little interest in connection to the topics under investigation. Moreover, as already observed in the previous section, the domain of *Multichannel Management*, which represents one of the trend research streams of the last decade in Marketing and IS, resulted in only one publication within our sample, concerning the implementation of e-commerce channels for AM.

2.2.5.4 Industrial Sector/Industry

The analysis of the sector/industries interested by the digital transformation shows results that can be clustered in **four main categories** (see Table 2.8, sorted in alphabetical order due to the high heterogeneity of the results). Indeed, 34 publications did not focus on a specific sector or industry, but provided applications and cases from *multiple sectors* among which Healthcare and Medical Industry, Jewelry, Dental Implants, Orthopaedics, Education, Automotive, Aerospace, etc. (Brennan et al., 2015; Campbell et al., 2012; O'sullivan et al., 2011; Sandström, 2016). Moreover, 26.7% of the overall sample (31 publications) presented studies concerning the broad *Manufacturing Sector*, in some cases focusing on a specific firm category such as: large enterprises (Milewski et al., 2015), SMEs (Dean et al., 2009; Rylands et al., 2016; Sommer, 2015; Wu et al., 2015) or multinational enterprises (Laplume et al., 2016).

Category	**Characterization**	**F**	**Tot**	**%**
3D Printing Industry	3D Printing	1		
	3D Printing Startups	2	3	2.6%
Aerospace Industry	Aerospace Industry	3		
	Aerospace Industry SMEs	2	5	4.3%
Automotive Industry		1	1	0.9%
Ceramic Industry		1	1	0.9%
Construction Industry		1	1	0.9%
Consumer Goods/Services		12	12	10.3%
Digital Trade		4	4	3.4%
Education Industry		2	2	1.7%
FabLabs		4	4	3.4%
Food Industry		1	1	0.9%
Footwear Industry		1	1	0.9%
Handicraft Industry		1	1	0.9%
Hearing Aid Industry		1	1	0.9%
Industrial Service Industry		2	2	1.7%
Lamp Industry		1	1	0.9%
Manufacturing Sector	Manufacturing Sector	21		
	Manufacturing Sector Large Enterprises	1		
	Manufacturing Sector Multinational Enterprises	1		
	Manufacturing Sector SMEs	8	31	26.7%
Multiple	Multiple	33		
	Multiple SMEs	1	34	29.3%
NGO		1	1	0.9%
No Industry Specified		8	8	6.9%
Plastics Industry		1	1	0.9%
Public Sector		1	1	0.9%
Total		116	116	100%

Table 2.8. Sectors Listed in Alphabetic Order

In addition, the 10.3% of the publications studied the effects of disruptive digital manufacturing technologies on the *consumer goods and services sector*. For instance, Steenhuis and Pretorius (2016) in their paper explore the adoption of consumer-level 3D printing and its potential disruptive impact on the existing manufacturing industry by investigating how competitive are consumer printed products compared to industrially manufactured ones (Steenhuis & Pretorius, 2016).

From the previous evidences it is clear that some important areas such as Public Sector (0.9%), Education and Industrial Service Industries (1.7%) and the FabLab network phenomenon (3.4%) received only limited investigation in the existing literature. To the latter can be added the 3D Printing Industry, which is related to the development and commercialization of different types of 3D printers (desktop, industrial, etc.), materials and connected services.

2.2.5.5 Research Method

Primarily based on research method stated in each article, the classification presented below was developed according to the authors. Only in the cases where this indication was missing the classification was made by interpreting the author's design. Indeed, in order to investigate whether the literature concerning the digital transformation of manufacturing is dominated by intuition-based reasoning and conceptual analysis (*Conceptual Research* category) rather than *Empirical Research*, a categorization was needed to classify the selected articles (Wareham et al., 2005; Scornavacca et al., 2006). In this analysis, "Empirical Research" was considered as all research originating in or based on direct observation or experience, including in some cases studies in which the researcher gathered data through secondary sources (e.g. case studies based on information collected from secondary data collection such as websites, databases, etc.). Mixed Methods studies include publications based on two or more different research methods, among them at least one is always empirical, which can employ either qualitative or quantitative research or both (Creswell, 2003). Articles characterized by intuition-based reasoning and academic literature reviews were classified as "Conceptual Research".

Looking at the aggregated frequency values, the sample appears split in two main groups with similar amount of studies, with a slightly higher percentage of empirical studies. Table 10 presents the distribution found in the sample. **Conceptual research** (46.6%) included articles based either on authors' subjective opinions and/or literature reviews and research commentary. As it will be analyzed more in depth in the next section, one paper classified as conceptual research in the category "Technology Assessment" (Gartner et al, 2015) was found to be based on primary data collection. The majority of the publications included in this macro-category were "Research Commentary" (34.5% of the entire sample), which results the main research method of our sample.

The frequency of methods in our sample indicates that **Empirical** articles are the most prevalent type of research (53.3%). Empirical articles were classified as those publications mainly relying on direct or field observations usually captured through several methodological research techniques such as case studies, field surveys, field studies/interviews, as well as laboratory and field experiments. By far, the most frequent research methods in this category were "Multiple-Case Study Research" and "Case Study" (respectively 12.9% and 7.9%). This evidence can be explained by the fact that phenomena and technologies under investigation are relatively young and present limited empirical evidence (Sandström, 2016), thus research is exploratory in nature. Because of this, an inductive approach based on explorative case studies was often adopted (Rayna et al., 2015). This kind of theory building research is not oriented towards general laws or correlations between dependent and independent variables, but instead aims to uncover the social dynamics and mechanisms that underlie certain processes. When based on multiple data-sources, this method allows for triangulation in order to enrich and corroborate the findings (Birtchnell et al., 2016; Eisenhardt & Graebner, 2007). Furthermore, the research questions identified are mainly "how" questions. Yin (1994) suggests the case study methodology is well suited to meet the requirements of answering "how" questions such as the ones raised in order to examine a contemporary phenomenon in context like the digital transformation of manufacturing. A case study is an objective, in-depth examination of a contemporary phenomenon where the investigator has little control over events (Rylands et al., 2016; Yin, 1994). Scholars have used case studies to develop theories about topics as diverse as group processes (Edmondson et al., 2001), internal organizations (Galunic & Eisenhardt, 2001), and strategies (Mintzberg & Waters, 1982). Building theories from case studies is a research strategy that involves using one or more cases to create theoretical constructs, propositions and/or midrange theories from case-based, empirical evidence (Cautela et al., 2014; Eisenhardt, 1989). For instance, Milewski et al. (2015) adopted an exploratory case-based research design and conducted a multiple-case study of five large successful manufacturing companies operating in different industries in Germany, in order to investigate the management of technological change, organizational change, and systemic impact at different stages of the innovation lifecycle (ILC) in large manufacturing companies (Milewski et al., 2015).

Following, the identical low frequency value (3.4%) of "Survey" and "Experiment" categories - typically characterized by a quantitative approach to research - highlights the lack of publications based on these methods in this field. This datum will be further analyzed in the research approach section.
In addition, within this category is interesting to note that none of the papers of our sample was grounded theory-based.
Table 2.9 shows the evidence presented in this section.

Category	*Sub-category*	*N*	*%*	*Σ*
Conceptual Research	Market Assessment	1	0.9%	
	Literature Survey	1	0.9%	
	Technology Assessment	3	2.6%	
	Literature Review	9	7.8%	
	Research Commentary	40	34.5%	46.7%
Empirical Research	Grounded Theory	0	0%	
	Action Research	1	0.9%	
	Focus Group	1	0.9%	
	Empirical Study	2	1.7%	
	Interviews	3	2.6%	
	Experiment	4	3.4%	
	Survey	4	3.4%	
	Case Study	9	7.8%	
	Simulation	10	8.6%	
	Mixed Methods	13	11.2%	
	Multiple-Case Study	15	12.9%	53.3%
Total		116	100%	100%

Table 2.9. Categorization of Research Methods

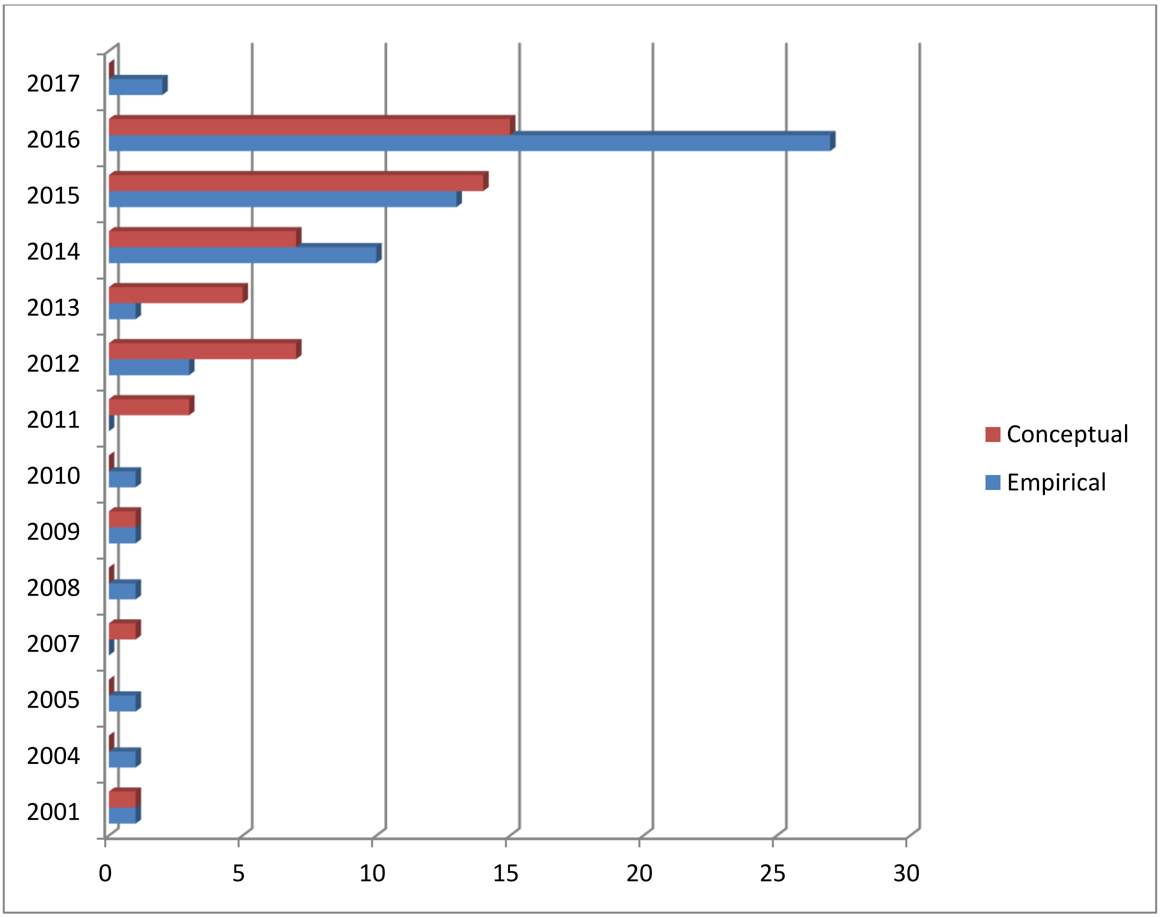


Fig.2.4. Research Method Distribution per Publication Year

The above chart (Fig. 2.4) represents the publications divided in the two main research method categories (i.e. conceptual and empirical research) and ordered per year. It is useful to observe the evolution through the considered time period of the publications in this field. In particular it is possible to observe an increase in the number of empirical publications in the last two-three years, not considering the year 2017 which was just started when the literature search was carried out. At the same time, in Fig.2.7 the same increasing trend is recorded concerning the number of publications based on secondary data.

2.2.5.6 Research Approach

Following Alavi and Carlson (1992), our primary papers were classified as *qualitative research* if they had an emphasis both on the description and understanding of the context and the environment of the research phenomenon (Alavi & Carlson, 1992). On the other hand, studies using numerical analysis to illustrate the relationship among factors in the phenomenon studied were classified as *quantitative research*. Studies that used both quantitative and qualitative methods were categorized as “mix”. Steenhuis and Pretorius (2016), in their explorative study on the adoption of consumer-level 3D printing and its potential impact, followed a two-method research approach. The authors initially used a qualitative research method similar to an in-depth exploratory case study to determine user friendliness and role of technological characteristics of a consumer-level 3D printer. On the other hand, they used a questionnaire-based survey as well as a bibliometric analysis as part of a triangulation strategy, to explore the adoption of 3D printer technology by consumers more broadly and confirm their previous conceptualizations through quantitative research.

Category	N	%
Qualitative	78	67.2%
Quantitative	17	14.7%
Mix	21	18.1%
Total	116	100%

Table 2.10; Fig 2.5. Research Approach Categories

Table 2.10 presents the distribution found in the sample. Clearly the most common research approach was *qualitative* (67.2%), which presents a value 4.5 times higher than the *quantitative approach*. This datum results coherent with the high frequency recorded by “conceptual research” category, typically characterized mainly by qualitative approaches, as well as the overall Case Study research (counting together Case Study and Multiple-Case Study) which resulted based on a qualitative approach for the 83% of these studies. In addition, twenty-one papers of the sample (18.1%) were based on a mix of qualitative and quantitative approaches (i.e. "mix" category in the table above).

Domain/Approach	Qual.	Quant.	Mix
Circular Economy	1	0	0
Consumer Research	2	0	1
Decision Making for Innovation	2	1	1
Education	3	0	2
Entrepreneurship and Business Research	2	0	2
Industrial Economics	1	0	2
Innovation (Process)	6	0	3
International Business Research	1	0	0
IP Law	4	0	0
MIS	3	2	1
Manufacturing Economics	2	0	0
Multichannel Management	1	0	0
Multiple	12	3	0
Organization Science	2	0	0
Product/Service Innovation	1	0	0
Production Economics	6	3	2
SCM-OM	8	7	2
Service Science	3	0	1
Sharing Economy	3	0	1
Strategic Management	3	0	0
Technology and Innovation Management	12	1	3

Table 2.11. Research domain Vs. Approach

The above table shows a cross-analysis between *domain* and *approach* categories, alphabetically ordered. The most significant evidences are represented by the relatively high frequency (12 publications) of *Technology and Innovation Management* domain in connection to qualitative research ("Multiple" domain research has an equal frequency value) and the research in *Supply Chain Management-Operations Management* that presents the highest frequency in terms of quantitative research (7 publications).

More in details, from table 2.12 it is possible to observe that *Research commentary* and *Multiple Case Study* research present the highest values in terms of qualitative studies, resulting almost in their entirety. In addition, the research method characterized by the highest frequency value of quantitative studies was found to be *Simulation.*

Method/Approach	QUAL.	QUANT.	MIX
Action Research	1	0	0
Case Study	6	2	1
Empirical Study	0	1	1
Experiment	1	1	2
Focus Group	1	0	0
Grounded Theory	0	0	0
Interviews	3	0	0
Literature Review	8	1	0
Literature Survey	1	0	0
Market Assessment	1	0	0
Mixed Methods	2	2	9
Multiple Case Study	14	0	1
Research Commentary	37	0	3
Simulation	2	7	1
Survey	0	1	3
Technology Assessment	1	2	0

Table 2.12. Research domain Vs. Approach

2.2.5.7 Nature of Data Collection

The present section concerns the distribution of data sources in our sample. It should be noted that about 67% of the publications were based on *secondary data collection* (see Table 2.13 and Fig. 2.6). Interestingly, this frequency has a value very similar to the frequency of publications based on a qualitative approach.

Category	F	%
Primary	34	29.3%
Secondary	77	66.4%
Mix	5	4.3%
Total	116	100%

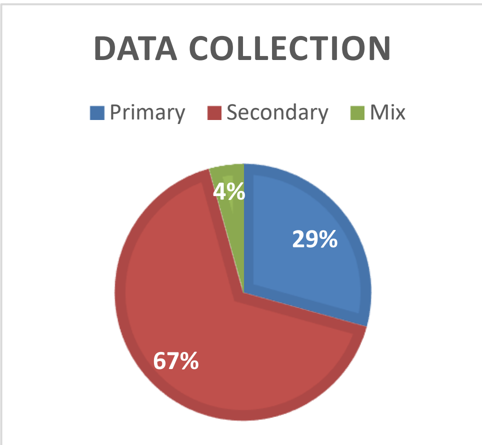


Table 2.13; Fig. 2.6. Nature of Data Collection Categories

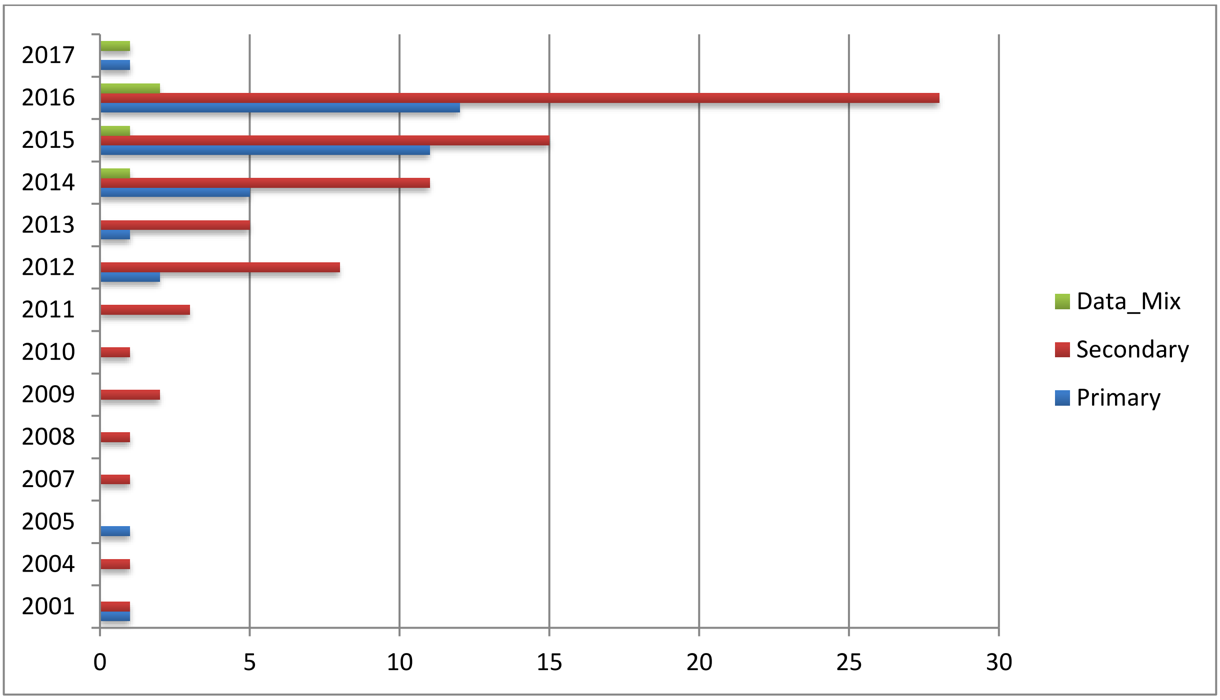


Fig. 2.7. Nature of Data Collection per Publication Year

Domain/Nature of Data Collection	Primary	Secondary	Mix
Circular Economy	0	1	0
Consumer Research	2	1	0
Decision Making (for Innovation)	3	0	1
Education	2	3	0
Entrepreneurship and Business Research	1	2	1
Industrial Economics	0	2	0
Innovation (Process)	2	8	0
International Business Research	0	1	0
IP Law	0	4	0
MIS	2	4	0
Manufacturing Economics	1	1	0
Multichannel Management	0	0	1
Multiple	5	10	0
Organization Science	0	2	0
Product/Service Innovation	0	1	0
Production Economics	2	6	0
Production Economics	0	2	1
SCM-OM	5	12	0
Service Science	2	2	0
Sharing Economy	3	1	0
Strategic Management	0	2	1
Technology and Innovation Management	4	12	0

Table 2.14. Domain/Nature of Data Collection Cross Analysis

The chart above (Fig. 2.7) represents the publications divided by the nature of data collection categories (i.e. primary, secondary, mix) and ordered per year. The figure shows clearly a constant increasing trend in the number of publications based on secondary data collection (the main category of the sample), not considering the year 2017 which was just started when the literature search was carried out. Furthermore, table 2.14 shows a cross-analysis between *domain* and *Nature of Data Collection* categories.

2.2.5.8 Main Contribution

An analysis of the main contribution of each article was also conducted. Many authors clearly highlighted the main contributions of their papers. However, as per other classifications, due to the lack of information given by the authors in some cases the present classification required a reviewer judgment. Table 2.15 shows the findings. The fact that “literature review” was the most common research method undoubtedly resulted in “insights” and to a lesser extent “frameworks” emerging as the most common type of contribution of the articles reviewed. Only 30% (18) of the papers that offered a framework as their main contribution are based on primary data collection.

Main Contribution	F	%
Theory Building	2	1.7%
Research Agenda	9	7.8%
Multiple	10	8.6%
Conceptual Model	17	14.7%
Conceptual Framework	33	28.4%
Insights	45	38.8%
Total	116	100%

Table 2.15. Main Contribution of the Sample Publications

The fact that “conceptual research”, and in particular *Research Commentary* was found to be the most common research method resulted in “Insights” (38.8%) and to a lesser extent in “conceptual Framework” (28.4%) as the most common types of contribution within the publications reviewed. Only two papers resulted in building new theory as main contribution (i.e. "Theory Building"). Moreover, ten papers showed a combination of more than one main contribution; for instance, (Brooks et al. , 2014; Campbell et al., 2012; Campbell et al., 2011; Dutton, 2014), present both “Insights” and “Research Agenda” as main contributions.

Table 2.16 presents a cross-analysis between “Focus” and “Main Contribution” categories.

Focus/Main Contribution	*Conceptual Model*	*Conceptual Framework*	*Insights*	*Research Agenda*	*Theory Building*
AM Features/Applications	0	1	10	3	0
Business Mode Innovation	2	5	1	2	0
Democratization of Manufacturing	1	5	11	4	0
Digital Knowledge Dissemination	1	2	1	0	0
Digital Transformation of Products/Services	3	0	2	1	0
Economic/Competitive Impact of Digital Transformation	0	0	6	1	0
Impact on Value Proposition	0	1	1	0	0
Intellectual Property Law	0	0	2	0	0
Manufacturing Supply Chain Reconfiguration	6	17	13	5	2
Multiple	0	0	1	0	0
Sustainability	0	1	1	1	0
Technological Development Dynamics	2	3	0	1	0
Technology Assessment and Comparison	2	0	3	1	0

Table 2.16. Focus/Main Contribution Cross Analysis

From this independence test results that:

- The majority of papers contributing with a *conceptual framework* were connected to the "Manufacturing Supply Chain Reconfiguration" focus;
- "Manufacturing Supply Chain Reconfiguration" is the only category presenting a theory Building contribution over the entire sample;
- Papers in the categories "AM Features/Applications" and "Democratization of Manufacturing" contributed mainly with *insights* to the current research in the field.

In addition, we found interesting to cross the results concerning method and contribution categories. Among the information derivable from table 2.17, the most meaningful are:

- *Research commentary* publications show the highest values in terms of "Insights" (30) and "Research agenda" (11) contributions. This evidence confirms the exploratory nature of this type of studies.
- *Simulation* results as the category with the highest score in terms of conceptual model as main contribution (5). Together with the relatively high frequency value for the conceptual framework type of contribution, this results show that this category of publications tends to contribute to the literature by offering concrete models or frameworks that can be useful for the development of future studies.

Method/Contribution	*Conceptual Model*	*Conceptual Framework*	*Insights*	*Research Agenda*	*Theory Building*
Action Research	0	1	0	0	0
Case Study	1	4	4	0	0
Empirical Study	0	1	1	0	0
Experiment	2	1	1	0	0
Focus Group	0	0	1	0	0
Grounded Theory	0	0	0	0	0
Interviews	1	1	1	0	0
Literature Review	1	2	3	2	1
Literature Survey	1	0	0	0	0
Market Assessment	0	1	0	0	0
Mixed Methods	2	5	5	1	0
Multiple-Case Study	0	8	6	2	0
Research Commentary	0	6	30	11	1
Simulation	5	4	0	1	0
Survey	3	0	0	1	0
Technology Assessment	1	1	0	1	0

Table 2.17. Method/Contribution Cross Analysis

The totals of the two previous tables are higher than 116 since publications with more than one main contribution were counted twice.

2.2.5.9 Geographical Distribution

Finally, our sample was analysed in terms of regional context of the publications. As abovementioned, the nationality of the research was assigned country based on the first author's affiliation. Table 2.18 shows the distribution of papers per country.

Country	N Publications	Country	N Publications	Country	N Publications	Country	N Publications	Country	N Publications
UK	18	Italy	4	India	2	Hungary	1	Serbia	1
USA	18	Denmark	3	Ireland	2	Malta	1	Sweden	1
Germany	16	Romania	3	S. Korea	2	Mexico	1	Taiwan	1
Finland	8	Switzerland	3	NL	2	Norway	1		
China	6	Austria	2	Belgium	1	Poland	1		
Australia	5	Brazil	2	Chile	1	Portugal	1		
France	5	Canada	2	Spain	1	RSA	1		

Table 2.18. Regional Context of Publications

By observing the previous table as well as the graphical representation provided by Figure 2.8, it is clear that the largest number of papers (18 each, corresponding to 15.5% of the sample) were written by researchers or academics working in UK and USA. In particular, the manufacturing sector is at the core of the American economy. With American leadership in advanced manufacturing at risk due to changes in the global economy and new competitors rising across the globe, the U.S. President Barack Obama in March 2012 announced an investment of $1 billion in the **National Network for Manufacturing Innovation (NNMI)** to support U.S. manufacturing innovation and encourage insourcing. Its key focus is on new technology paradigms that can improve the competitiveness of American manufacturing – with a focus on small and medium enterprises (SMEs) – through digitization of design and manufacturing, democratization of technology, and collaborative design and analytics to sustain leadership across the U.S. manufacturing ecosystem (Beckmann et al., 2016). This settings would have pushed American universities, companies and institutions in orienting scientific and professional research to these subjects.

A similar background makes Germany be the third country for number of publications within the analyzed sample, with a frequency value of 16 (%). Germany relies heavily on manufacturing to fuel its economy as well as Europe. Twenty-two of its top 100 small and medium-sized enterprises are machinery and plant manufacturers, with three of them among the world's top 10. "Industrie 4.0", Germany's response to the so-called "fourth industrial revolution", is a cornerstone of the German government's industrial 2020 high-tech strategy, initiated by Industry Science Research Alliance. Research is essential to realize all the initiatives needed for the industrial digital transformation, and plenty of funding will be needed. The idea has already spurred collaboration in Germany's research community. Electronics and engineering giant Siemens has formed an industrial automation and digitization research alliance with the state funded Technical University Munich (TUM), Ludwig-Maximilians University (LMU), the German Research Center for Artificial Intelligence (DFKI) and the Fraunhofer Institute for Applied and Integrated Security (AISEC). Doctoral and postdoctoral programs offered by the technical universities will enable up to

100 doctoral candidates to pursue their studies while collaborating on automation and digitalization research (Blau, 2014). These growth strategies have certainly strongly influenced the scientific production in this field.

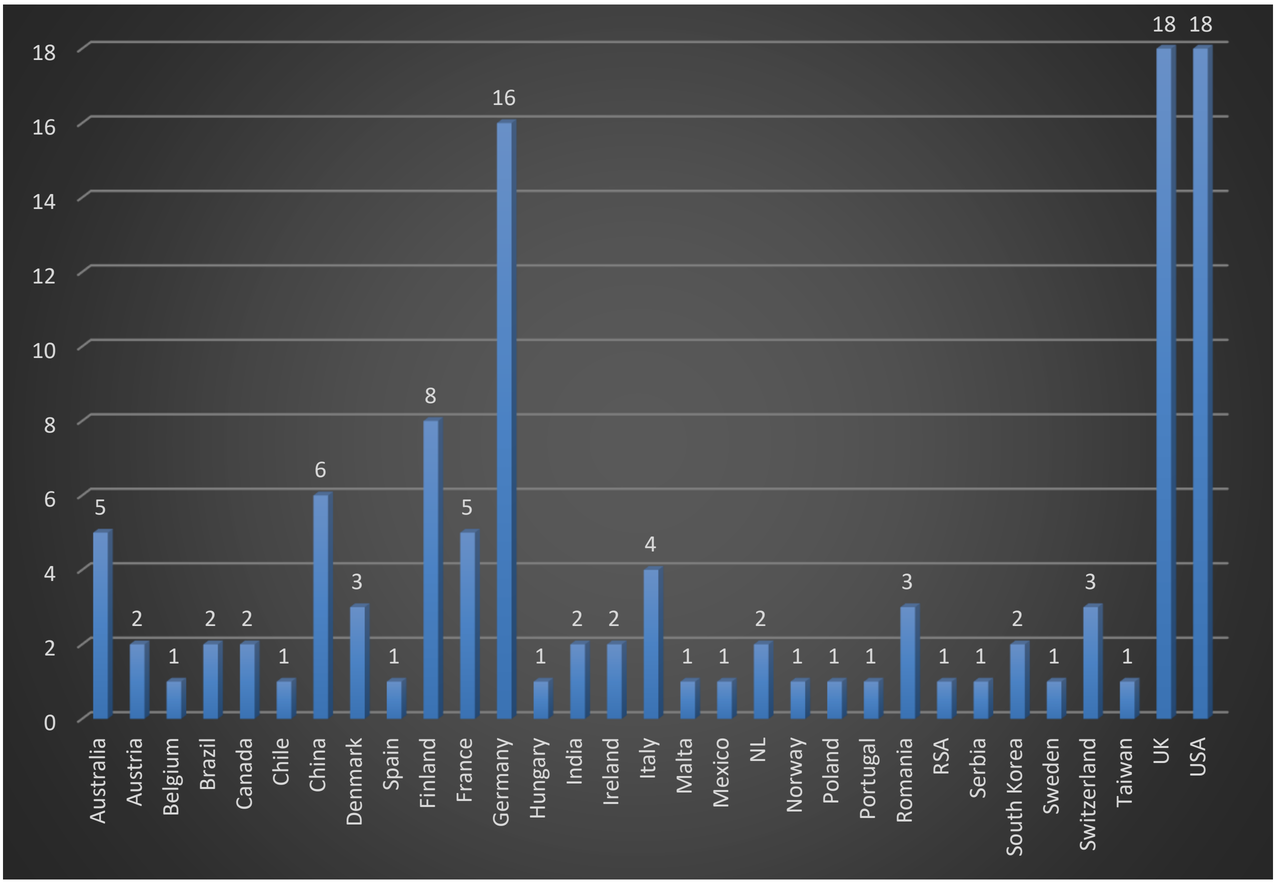


Fig.2.8. Chart of the Regional Distribution of Publications

2.2.6 Conclusion and Future Research Paths

This section shed lights on past and current research into the digital transformation of manufacturing, in order to provide a broad picture of this field through a categorization and statistical analysis of scholarly journal publications. The findings presented above provide evidence that there is an increasing interest of researchers from different research domains as well as a rapid growth of the body of literature in the last years connected to the parallel technological evolution of the sector mainly due to the huge investments in innovation made in USA, Europe and many other industrialized countries of the world.

As observed, the applicability of digital manufacturing technologies varies considerably across the different industries in the manufacturing sector and presents a growing number of technical tools, managerial strategies as well as end-users' applications. In some industries - or industry segments - digital manufacturing is technologically, but not economically feasible. The analysed literature shows that the diffusion of digital manufacturing in a certain industry is often associated with a development toward shorter and more dispersed global value chains. Hence, in some industries this new ecosystem is likely to pull manufacturing value chains in the direction of becoming more local, and closer to the end-users (Laplume et al., 2016). Anyhow, these assumptions would need a great deal of efforts in terms of research to confirm and determine the dimensions of this trend.

From the present systematic literature analysis and mapping of the extant literature, some important **patterns** and **gaps** have been highlighted:

- *Within our sample it was found an high concentration of articles focused on AM technologies employed in the reconfiguration of Operations in the Manufacturing Supply Chain*.
  Some specific topics as the consequent innovation of business models and value chain activities, as well as the digitalization of customized one-offs products leading to an integration of customers/end users in the manufacturer's supply chain, received limited investigation;
- *The slight majority of studies were empirical, although the sample resulted well balanced between both empirical and conceptual categories.* Within this last broad category a high number of papers were found to be "research commentary", which represents the largest category of the whole sample. Moreover, the important lack of systematic literature analysis/survey as well as the total absence of Grounded Theory studies has to be mentioned. In the light of this result, the present systematic analysis of the literature appears to be necessary;
- *Publications resulted characterized mainly by exploratory Qualitative Research,* based in the large majority of cases on *Secondary data collection;*
- *Empirical studies were strongly dominated by Exploratory Case study Research.* The analysis of the distribution highlighted an important lack of quantitative survey and experimental studies;
- *From the analysis of the main contributions resulted a high frequency of "Insights"; a lack of "theory building"* contributions (which would involve to test predictive/conceptual research models) was observed.

As the body of literature concerning the digital transformation of manufacturing grows, this area of research is likely to mature and develop a research tradition of its own. However, our analysis suggests that for this outcome to happen, researchers in this field should begin to focus their efforts more carefully. In particular, according to the gaps found in the literature, the following areas are promising candidates for **future research**:

- Research focused on the *impact of AM on Value Chain activities*, with important possible implications on the re-organization of internal business functional units. This topic is connected to the involvement of customers and end-users in the creation of customized products through a multichannel strategy;

- In connection to the previous point, more relevant research is needed in the area of *Business model Innovation and value creation/capture*. These topics are closely linked, since a company's business model describes its logic of creating and capturing value (Afuah, 2014; Osterwalder & Pigneur, 2010; Zott et al., 2011). There is a growing consensus that 3D printing technologies, and more in general digital manufacturing, is going to be one of the next major technological revolutions. While a lot of work has already been carried out as to what these technologies will bring in terms of product and process innovation, little has been said on their impact on business models and business model innovation (Rayna & Striukova, 2016). While much more value can be created, capturing value can become extremely challenging. Hence, research should focus on finding a suitable business model to capture this value;
- *Quantitative research based on Primary data collection*: the existing body of literature involves a disproportionately high level of research characterized by qualitative studies based on secondary data collections. More research based on quantitative studies (i.e. surveys and model testing) has to be carried out in order to address this gap;
- *Specific Topics:* the comprehensive concept of *Sustainability* of technology and reconfigured business processes, *Intellectual Property Law* issues connected to the online trade of digital projects/models, as well as the *Educational* perspective about Digital Knowledge Dissemination represent interesting fields that need more attention from researchers;
- *Impact on Performance/Competitive Advantage:* we found very few literature concerning the impact of this new ecosystem on business and organizational performances intended as *Sustainable Competitive Advantage (SCA), Enhanced Value Proposition, Customer Satisfaction, Market Share, etc.* In order to understand and measure this impact it would be necessary to understand how this disruptive change can confer or drive organizations to build essential dynamic capabilities, in order to allow them to successfully compete in highly competitive and turbulent business environments;
- *Theory Development*: in order to gain a solid theoretical foundation, this field needs contributions aimed at creating specific theories, in addition to the application of solid existing reference theories.

Finally, some limitations also characterize the present literature analysis. While our sampling has been extensive, it could be not fully comprehensive. Indeed, as abovementioned we included only peer-reviewed publications from scholarly journals in our sample, excluding many other potentially excellent papers not included in this category (e.g. conference proceedings, etc.). Moreover, our search criteria may be incomplete since some papers that do not have the terms used for the keyword literature search may not have been included. In addition, sometimes it was necessary to interpret the articles during the coding scheme, in order to classify them within our coding scheme. This process, although was carried out in the most rigorous possible way and only in cases where the authors had not explicitly stated the nature of their research, may result in source of bias in the evaluation of the articles.

In conclusion, results achieved and discussed so far were able to address the main research question and sub-questions of the present literature analysis. The intention of this stage was to take stock of existing research and extend the research on digital manufacturing by drawing on its foundations. In doing so, this study seeks to propel more focused theory building and discussion about its implications both on the development of required capabilities and organizational performance.

2.3 Literature Review

Based on the evidence resulting from the systematic literature analysis, some important patterns and gaps concerning the literature on *digital manufacturing* have been highlighted.

It is interesting to emphasize that, given the multidisciplinary nature of the topic of interest, this section discusses and analyses themes and constructs that form the foundations for this research through a summary of studies drawn from different disciplines (e.g. IS, Management, Organization Science, Psychology, etc.).

The purpose of this section is to establish a strong theoretical foundation to address the research question that drives this study. In order to achieve this goal, it is crucial firstly to define the concept of Digital Manufacturing.

Furthermore, for analysing the impact of digital manufacturing on organizational performance, this study seeks support in the *disruptive innovation theory* and investigates this phenomenon through the resources-processes-values (RPV) framework.

In addition, to deeply understand how firms develop digital capabilities to obtain a competitive advantage, relevant literature on dynamic capabilities (i.e. Dynamic Capability View and antecedent theories) and firm's specific resources will be reviewed.

Finally, a refined version of the conceptual research model will be presented, reflecting the key themes found in the literature and the relevant propositions developed.

2.3.1 Digital Manufacturing

This first part of the literature review presents the definition of the key terms used for the literature search, aiming at understanding the digital manufacturing concept, analyzing also the notion of *digital ecosystem*. Section 2.3.1.2 provides the definition of the concept of *digital manufacturing ecosystem*.

This research focuses on the digital transformation of manufacturing and on the impact this complex phenomenon has at firm level as well as on the ecosystem of stakeholders around it (i.e. consumers, governments, etc.). Digital manufacturing – which includes the concepts of additive manufacturing (AM), rapid prototyping (RP), 3D printing and Industry 4.0 (also known as Smart Manufacturing)- has the potential to revolutionize the way in which products are designed, produced and delivered to the customer (Bogers et al., 2016). Therefore, it challenges companies to reinvent their business model, describing the logic of creating and capturing value. Indeed, Manufacturing sector is currently evolving toward digitalization, network and globalization (Lan, 2009). Among the concepts and elements that represent this paradigm shift, based on the existing literature, the following ones were chosen as the most representative. This section provides a definition of each of the three keywords used in the literature analysis search, crucial in order to have a clear understanding of the further analyses:

- *Digital Manufacturing (DM)*: it is an umbrella concept, which encloses more than one aspect of this new scenario under investigation. While the move towards digitalisation of manufacturing – also known as digital fabrication – started decades ago with the progressive adoption of CAD (Computer Aided Design), CAM (Computer Aided Manufacturing), CNC (Computer Numeric Control) machines and other computer-controlled manufacturing systems, the trend has significantly accelerated over the past few year, in particular because of the advent of 3D printing technologies (Rayna & Striukova, 2016). The connected concept of *digital fabrication* (DF) is described as an emerging industry that applies computer-controlled processes and tools to create useful physical products from digital data (Potstada et al., 2016). As *direct digital manufacturing* (DDM), this concept describes processes that directly transform 3D data into physical parts, without any need for tools or molds (Weller et al., 2015). DDM, which corresponds to manufacturing end-use products through 3D printers, and *home fabrication* - which refers specifically to the use of personal 3D printers - were found to be potentially more significantly disruptive in terms of increase in value creation/delivery and impact on business model innovation (Rayna & Striukova, 2016). It shows applications both in demand side and supply side (i.e. industrial production) contexts. This study focuses mainly on the industrial context, by analyzing the dynamics of the manufacturing sector.
- *Additive Manufacturing (AM)*: refers to the "process of joining materials to make objects from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing methodologies"

(ASTM, 2012) and fits in the wider context of digital manufacturing (Caputo et al., 2016). AM is not just a single technology. Instead it encompasses a wide range of technologies and connected software, each at different levels of technological maturity, offering the option of using an ever growing variety of materials, with different quality outputs. This process represents a compelling alternative to the conventional "subtractive manufacturing", in which excess material is removed to make the finished item. It offers ground-breaking opportunities to manufacture items with improved functional and aesthetic properties over those produced using the traditional method. It can not only make objects which would be practically impossible by traditional methods (i.e. complex shapes), but also completely new products (Brennan et al., 2015). Due to these characteristics, nowadays AM has a wide range of applications in several industries and fields of human activity: research, engineering, medical industry, military, aerospace, automotive, jewelry, construction, architecture, fashion, education, food and many others. (Pîrjan & Petrosanu, 2013). For its disruptive potential AM has been hailed by some scholars as the "*Third industrial revolution*" (The Economist, 2012) with the potential of transforming global society and everyday life (Lipson, 2012). In industrial contexts AM is the accepted term, while 3D printing is commonly used to denote those machines (i.e. 3D printers and scanners) employed primarily by home users and for consumer goods (Ford et al., 2016). This latter term refers not only to the technology but also to online 3D printing platforms which already provide significant means for consumers to take advantage of other peers' innovations within communities of users (also known as "makers") (Rayna et al., 2015). 3D printing technologies can be involved at different stages and to a different extent in the production process, corresponding to four progressive stages of adoption: rapid prototyping (RP), rapid tooling, direct manufacturing and home fabrication (Rayna & Striukova, 2016). Past research demonstrated that 3D printing is most advantageous in market environments characterized by demand for customization, flexibility, design complexity, and high transportation costs for the delivery of end products (Weller et al., 2015; Birtchnell et al., 2016).

As observed in one of our recent works (Savastano et al, 2015), AM technologies offer several important advantages to manufacturer companies:

- to redesign products with fewer components, reducing material waste as well as obtaining lighter parts characterized by equal physical strength properties;
- to realize products on-demand closer to the customers (the so-called "distributed manufacturing"), simplifying the traditional supply chain and reducing delivery times together with warehousing, packaging and transportation costs;

- to produce any good - including customized ones - in small production batches (even batches of one) economically, with an enhanced flexibility in terms of locations and times. This could potentially cut off costly inventories of semi-finished and finished goods.

In particular, if compared to traditional production techniques, additive manufacturing exceeds any technical constraints related to the objects geometries, enhancing conventional flexible manufacturing systems (FMS) advantages (Weller et al., 2015). Complex shapes realized as one piece in a single run (i.e. one-step manufacturing process), with no assembly required, result not only in lower costs of labor per unit due to a decrease of production stages, but also in higher level of technical functionality and shorter lead times (D'aveni, 2015). Thus product designs can be optimized according to their desired function rather than restricted from production technology or supply chain constraints (Berman, 2012). New materials, together with these novel production technologies allow greater manufacturing flexibility, especially in the customization of products and by making goods more efficiently in lower volumes. This means it is convenient for companies to locate closer to the market they sell into, therefore products can be tailored more specifically to those markets and they can respond to changing trends much faster (Franklin, 2017).

At the same time, production costs are nearly independent from the volumes. In fact, since each unit is built independently, it can easily be modified only by changing the digital design in order to accommodate improvements, demand variability or to suit unique requests. Combining these benefits with the enormous availability of data concerning customers needs, behavior and preferences, as well as the possibility to directly interact with them through several digital touchpoints, companies are able to achieve high degrees of product customization, with the possibility to delight customers by involving them in the co-design of goods (Reeves, et al., 2011). Consequently, product variety can potentially become infinite without incurring in additional costs of manufacturing. Moreover, by matching customer preferences, customized products potentially yields an increase in customers' perceived value, and thus higher willingness to pay (WTP) (Franke et al., 2009).

On the other hand, these opportunities are still counterbalanced by a number of limitations in terms of higher costs of available materials, choice of colors and surface finishes, physical limits to products dimension, relatively low production speed, precision and lack of quality and safety standards. Furthermore, since economies of scale are not feasible through this technology, it is not competitive in terms of costs for large scale production of standardized goods. This makes it suitable especially for small-scale and high-quality local productions characterized by a premium price, whereas the mass production of standardized parts currently remains the domain of conventional manufacturing techniques. Although there are still clear limitations, AM technology recently made enough advances to become a viable manufacturing methods for end-use components in certain applications. Particularly, several studies have specifically focused on the potentialities of AM and digital manufacturing in the context of spare parts supply chain, by paying specific attention at the possibility of producing them closer to the point of need thanks to these innovations (Li et al., 2017; Pérès & Noyes, 2006).

Table 2.19 shows schematically the complete list of advantages and limitations of digital manufacturing technologies from three different perspectives as resulting from the review of both academic literature and practitioner based research reports, according to a technological and economic point of view.

	Advantages	Limitations	References
Supply Side	– Enhanced production flexibility in terms of locations (distributed production, in-situ 3-D printing) batch sizes (batch size of one) and product designs without cost penalty in manufacturing – Reduced costs of logistics – Simplified supply chains: shorter lead times, reduced production downtimes and lower inventories – Direct digital manufacturing of 3D digital designs in one-step, without the need for tools or assembly – On demand production: no unsold products – Increase of design complexity without cost penalty in manufacturing – Higher products' performances – Price premiums achieved through customization or functional improvement (e.g. lightwait) of products – Lowering barriers to market entry	– No economies of scale – Higher marginal costs of production (row material and energy intensity) – Low production throughput speed – Skilled labor and strong experienced needed – Training effort required – Missing quality standards – Significant effort still needed for surface finishing – Intellectual property rights and warranty related limitations – Lack of design ools and guidelines to fully exploit possibilities of AM	– Berman, 2012; – Brody & Pureswaran, 2013; – Galli & Zama, 2014; – Gibson, et al., 2010; – D'aveni, 2015; – Gershenfeld, 2008; – Kietzmann et al., 2015; – MaRs, 2013; – Royal Academy of Engineering, 2013; – Petrovic et al., 2011; – PwC, 2015; – Reeves et al., 2011; – Weller et al, 2015; – Wohlers, 2013; – Gebler et al., 2014; – Sirichakwal & Conner, 2016.
Demand Side	– Reduced delivery times and improved response speed (↑ efficiency) – Highly customized goods and higher product variety (without cost penalty in manufacturing) – Product co-design and co-creation – Consumer self-production	– Relatively high prices and limited diffusion of 3D printers – Product offering limited to technological feasibility (solution space, reproducibility, quality, speed)	
Ecological Footprint	– Reduced pollution, energy consumption and material waste		

Table 2.19. Advantages and Limitations of AM Technologies from Different Perspectives (Source: our elaboration)

– *Industry 4.0*: this term was born from a German initiative focusing on industrial production that promotes the computerization of traditional industries, aimed at designing intelligent factories characterized by adaptability, efficiency, functionality, reliability, safety and usability, while striving to integrate customers and business partners in business processes and value chains (Trentesaux et al., 2016). Factories are about to become smarter and far more flexible, able to respond to accelerating innovation cycles and designed to slash production costs (Blau, 2014).

It literally stands for "fourth industrial revolution" and represents the ongoing evolution and future of smart factories and industrial networks on the basis of collaborative *cyber-physical systems* (CPS), that is the merge of physical and the virtual worlds (Sommer, 2015; Wagner & Walton, 2016). It can be described as a smart manufacturing networking ecosystem where machines and products interact with each other even without human control (Ivanov et al., 2016). Driven by the Internet of Things (IoT) and based on the large use of digital manufacturing applications, ICT and Cloud computing, Industry 4.0 arguably represents the most revolutionary change to impact the manufacturing sector for some time, with businesses driven to pursue digital models that embrace connectivity, data analytics and customer focus. (Jones, 2016). These developments do not only have technological but furthermore versatile organizational implications (Lasi et al., 2014). In addition, It is worth noting that terms like "*Industrial Internet*" and "*Smart Manufacturing*" have different geographic origins but substantially the same meaning of Industry 4.0 (Chand & Davis, 2010; Fox, 2015; Lohr, 2011).

The concept of Industry 4.0 is seen as an important strategy to remain competitive in the future. Industrial companies are currently facing the challenges of increasing customization, individualization of products and flexibility of production, the need to increase the resource efficiency, and reducing time-to-market. These challenges can be addressed in particular with increasing digitization, IT penetration and networking of products, manufacturing resources and dynamicity of processes (Rennung et al., 2016). The successful implementation of such an industrial revolution is expected to take place in large enterprises as well as in SMEs.

In particular, literature on this topic highlighted some specific settings that drive the configuration of Industry 4.0 (Geissbauer et al., 2016):

1) **Digitization and integration of vertical and horizontal value chains**

(i) vertical integration of processes spans across the entire organisation, from procurement and product development, through manufacturing, logistics and services. All data about operations processes, process efficiency and quality management, as well as operations planning are available in real-time, supported by smart sensors and augmented reality and optimized in an integrated system; *(ii) horizontal integration* stretches beyond the internal operations, from suppliers to customers, including all key network partners. The organization in collaborative networks multiplies the available capacities without the need of further investments. Collaborative Manufacturing and Development Environments are important particularly for SMEs with limited resources; in fact, within these networks risks can be balanced and combined resources can increase the range of perceivable market opportunities (Brettel et al., 2014; Lin et al., 2012; Mendikoa et al., 2008).

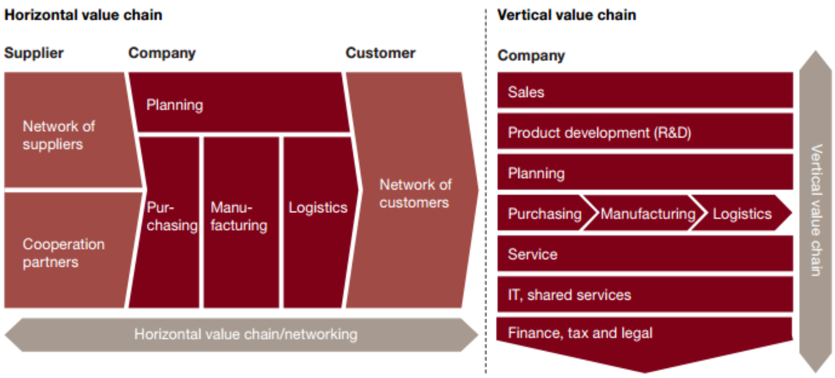


Fig. 2.9. Horizontal and Vertical Value Chains (Source: PWC 2015)

2) **Digitization and customization of products and services**

digitization of products refers to the expansion of existing products, for instance by adding smart sensors or communication devices to be used with data analytics tools (i.e. smart products), as well as to the development of brand new digitized products through entirely digitalized processes. By integrating new methods of data collection and analysis with flexible processes enabled by Modularization, Rapid Manufacturing techniques and Reconfigurable Manufacturing Systems, companies are able to generate data on product use and quickly refine products requirements to meet the increasing needs of end-customers in a cost-efficient way. Thus, both customer and suppliers are involved in the product innovation.

3) **Digital business models and customer access**

Leading industrial companies can also expand their offering by providing disruptive digital solutions such as complete, data-driven services and integrated platform solutions. Innovative digital business models are often focused on generating additional revenues and optimizing customer interaction and access. Digital products and services allow enterprises to serve customers with complete solutions in a distinct digital ecosystem.

Recent studies described also a set of *key technology trends* as the building blocks of Industry 4.0, which enable manufacturers to reach technical and economic benefits through faster, more flexible, and more efficient processes for the production of higher-quality goods at reduced costs. Many of the following advances in technology (such as additive manufacturing, smart sensors, advanced human-machine interfaces, big data analytics, data processing systems, etc.) are already employed by manufacturers, but within this comprehensive framework and by developing *ad hoc* expertise they will transform the production process: isolated cells will work together as a fully integrated, automated, and optimized production flow, leading to greater efficiencies and changing traditional production relationships among suppliers, producers, and customers - as well as between human and machine (Rüßmann et al., 2015). A representation of the majority of these essential innovative tools is shown in the following Figure 2.10.

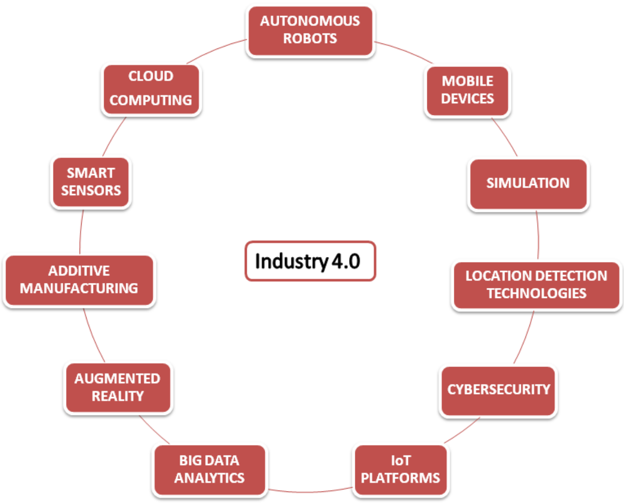


Fig. 2.10. Industry 4.0 Enabling Key Technologies (source: Savastano et al., 2016)

The rise and integration of the above mentioned basket of new digitally-enabled industrial technologies results thus in a new fundamental paradigm shift of the industrial production. This transformation includes advances in production equipment (i.e. additive manufacturing, autonomous and collaborative robots, adaptive CNC mills, etc.), smart finished products and objects (e.g. connected cars, ubiquitous computing and the Internet of Things - IoT), data tools and analytics, etc. In addition to these innovations, collaboration platforms, social networks, augmented reality, virtualization, cloud computing and crowdsourcing impact manufacturing companies and supply chains to varying degrees, changing the way things are designed, produced and serviced around the globe.

2.3.1.1 Digital Ecosystems

Typically, the notion of "ecosystem" provides a basis for understanding how capabilities and roles co-evolve and align over time in an innovation or business setting (Moore, 1993).

Selander et al. (2013) have defined digital ecosystems as "*a collective of firms that is inter-linked by a common interest in the prosperity of a digital technology for materializing their own product or service innovation*". The co-evolution between the technology and ecosystem participants creates self-reinforcing feedback loops that can affect the ecosystem either positively or negatively, making members both collaborators and competitors (Moore, 1993; Selander et al., 2013; Walley, 2007).

Ecosystems are closely related to Platforms. Accordingly, Simon (2011) defined a platform as "*an extremely valuable and powerful ecosystem that quickly and easily scales, morphs, and incorporates new features, users, customers, vendors, and partners*" (Simon, 2011). Moreover, the company-platform has been described as a new business model that uses novel digital technologies to connect people, organizations, and resources to an interactive ecosystem where remarkable amounts of value can be created and traded (Parker et al., 2016).

As recently reported by de Reuver et al. (2017), Iansiti and Levien (2004) in their work explore the strategic options for enterprises in becoming a keystone actor - i.e. platform - cultivating an ecosystem (Iansiti & Levien, 2004). Their study, building on the idea of Moore et al. (1997) of a changing competitive environment, thus applies the biological ecosystem metaphor to describe business ecosystems. While Iansiti and Levien's conceptualisation does not involve a platform construct, much other management research on ecosystems does. Some scholars use ecosystems to denote the organizational form associated with an industry platform (Gawer, 2014) or as an unspecific notion of a collection of assets (Thomas et al., 2014). Within management research, platforms are sometimes treated separately from and sometimes intimately related to the ecosystem construct or metaphor (de Reuver et al., 2017).

Thus, the **digital ecosystem** represents the dynamic environment where focal (typically a platform owner) and non-focal actors (defined as an "ecosystem participant who is at the periphery of the digital ecosystem") compete. For instance, some years ago Nokia could have been considered a non-focal actor in the Windows Phone ecosystem (Nokia released their first Windows-based phone in October 2011), although this ecosystem would have not survived without having any participants on the device layer (Selander et al., 2013). Within this environment, *innovation habitat* denotes the collection of resources and environmental conditions that defines a firm's scope of innovation in a given moment (Weddell, 2002). Selander et al. (2013) refer to *capability search* as a firm's activity of locating external capability deemed valuable for extending its innovation habitat. As indicated in the figure below (Fig. 2.11), capability search is dynamic rather than linear; it involves iterations where results of the initial search serve as input to new searches.

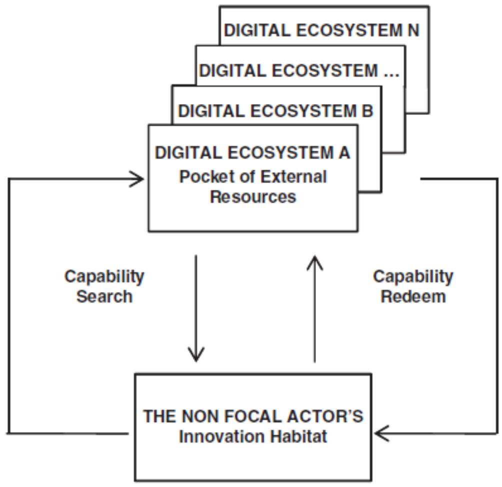


Fig. 2.11. Example of Ecosystem Capability Search and Redeem (Source Selander et al. 2013)

Pockets of external resources serve for capturing the subsets of ecosystem resources that allow a non-focal actor to develop new innovation capability. Examples of such resources include specific competences, technologies, and distribution models. However, not every non-focal firm possesses the capability to turn a set of ecosystem resources into a capability that enriches its innovation habitat.

At the same time, a non-focal firm not only needs to master capability search but also capability redeem. The literature refers to *capability redeem* as a firm's activity of cultivating its innovation habitat with external capability for developing, distributing, and/or monetizing its products and services.
Relying on external resources across ecosystems is a strategy to leverage inbound firm innovation by extending its scope of innovation (West & Gallagher, 2006; Yoo et al., 2010).

The power and success of a digital ecosystem depends on a collective of firms having a shared interest in its focal technology. The value of these ecosystems is based on the interactions and exchanges that occur within different players, allowing a set of relationships between companies, organizations, individuals which disclose the power to redesign the operating models of companies as well as the entire economic and industrial sector (Darking et al., 2008; Wareham et al., 2014).

2.3.1.2 Defining the Digital Manufacturing Ecosystem

The examination of the above definitions as well as the key terms used during the past decade and related to them provide substantial evidence to present a contemporary comprehensive definition of digital manufacturing ecosystem. Thus, for the purposes of this study, the rise of *digital manufacturing* is understood as:

A disruptive innovation of manufacturing process driven by an extended set of disruptive digital tools and internet technologies, which reshapes the way goods are designed, produced, delivered and updated as well *as the relationships among all the different actors of the Manufacturing Value Chain (i.e. suppliers, producers, retailers, consumers, competitors, etc.).*

Consequently, deriving from the above definition of digital manufacturing as an extensive *ecosystem* that includes different value activities and business functions, specific technologies (e.g. 3D Printing, Cyber-physical systems, IoT, Smart Products, Digital Platforms, Advanced Robotics, Cloud Computing and Data Analytics, etc.) and definitions (e.g. Additive Manufacturing, Digital Fabrication, Home Fabrication, Prosumption, Industry 4.0, Smart Manufacturing, etc.) for the purposes of this study are characterized as constitutive elements of this context.

Now that digital manufacturing has been defined, we can proceed with the other domains connected to this topic.

2.3.2 Disruptive Technological Change

In this section, an investigation of the literature concerning the impact of *disruptive digital innovations* on business resources and settings is carried out through disruptive innovation theory and the RPV framework (Christensen, 1997), in order to understand the factors that create dynamic capabilities as well as the need of building specific digital manufacturing capabilities for responding to the digital disruption. This stage is useful to understand companies' strategic reply to the digital transformation of its environment.

In a quickly changing and uncertain world, innovation is the key to competitive Advantage. At the same time, despite the successful implementation of innovations, only a few companies understand what is necessary for successful innovation (Assink, 2006).

The concept of *Innovation* covers a continuum from incremental or sustainable innovation (i.e. remodeling functionality) to radical or disruptive innovation (i.e. breakthrough, paradigm shift). Incremental innovation development remains within the boundaries of the existing market and technology or processes of an organization (see figure 2.12 below, lower left quadrant) and carries lower financial and market-acceptance risks.

Concerning the object of innovation, it can be classified as things - products and services - or as changes in the way products and services are created and delivered (i.e. processes). Johne (1999) distinguishes product and process innovation from market innovation (Johne, 1999). Among *process innovation* types can be cited innovation of the organization, transactions, management style and business model (Higgins, 1995; Paap & Katz, 2004; Slappendel, 1996). Innovation can also be distinguished by aggregation level: it can take place at an individual level (i.e. improvement), at functional level (i.e. process improvement or adaptation), at company level as an entire value chain (i.e. radical product and service innovation, new business models), and at industry level (i.e. technology breakthroughs) as systems of innovation (Assink, 2006; (Edquist, 1997).

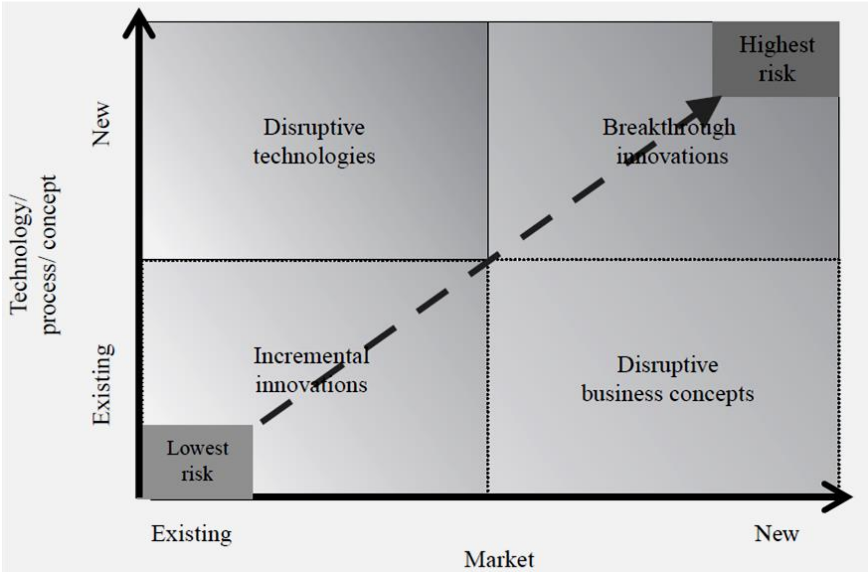


Fig.2.12. Innovation Applications (source: Assink 2006).

Technical innovation does not create value directly; it only creates change in processes, functionality or utility. It is the extent to which internal operations or external customers value a change, that leverage is created (Paap and Katz, 2004).

Disruptive innovation theory offers the explanations why companies succeed or fail to respond to disruptive innovations (Karimi and Walter, 2015).

Christensen (1997) in his seminal and path-breaking work developed a powerful framework for evaluating innovations and choosing business strategies to respond to technological change (Dombrowski & Gholz, 2009). The author stated that disruptive technologies bring to a market a very different value proposition than had been available previously. In contrast with "sustaining technologies" - new technologies that foster improved product performance - *disruptive technologies* generally underperform established products in mainstream markets. On the other hand, they have other features that a few fringe (and generally new) customers value. Products based on disruptive technologies are typically cheaper, simpler, smaller, and, frequently more convenient to use (Christensen, 1997). Furthermore, these innovations are competence-destroying, since they generate discontinuities that require users or adopters to change their behaviors in order to make use of them. They are also likely to be disruptive to the established incumbents by creating new-to-the-world products (e.g., 3.5-inch hard drives, personal computers, discount airlines, smartphones, online banking, mobile platforms, etc.). The new product first encroaches on the low end of the existing market and then diffuses upward, or may perform better on an alternate dimension and thus open up a new market (Schmidt & Druehl, 2008). Indeed, a technology can be considered disruptive when its use generates services or physical products with different attributes that may not be valued by a company's current customer base. These innovations often modify the basis of competition either by changing the performance matrices along which firms compete or by altering the positions of players in firms’ value networks. (Karimi & Walter, 2015).

The literature on discontinuous innovations also studied incumbents' resources and capabilities trying to explain their difficulties in responding to these innovations. Henderson (1993) suggests that incumbents invest more in incremental innovation than in radical innovation and are significantly less effective than entrants in their efforts to introduce radical innovations successfully, such that it makes their existing capabilities obsolete (Henderson, 1993). Christensen proposed an alternative clarification for the recurrent pattern of incumbent’s failure to respond to disruptive innovations by framing disruption as a theory. Christensen's work starts from *resource dependence theory* (Pfeffer & Salancik, 1978) which posits that companies’ freedom of action is limited to satisfying the needs of those entities outside the firm (i.e. customers and investors, primarily) that give them the resources they need to survive. Based on this theory, organizations will survive and prosper only if their staff and systems serve the needs of customers and investors by providing them with the products, services, and profit they require. Organizations that do not will ultimately fail, starved of the revenues they need to survive (Christensen, 1997).

Assink (2006) proposed a conceptual model on disruptive innovation capability to provide a better understanding of the internal/eternal inhibitors or barriers many large corporations encounter to develop or adopt disruptive innovations. Developing distinctive capabilities, and in particular disruptive innovation capabilities, should be an integral part of a company’ strategy for growth since future success has much to do with a company’s innovation capability. The author found that in general, most large corporations lack the management ability to adapt the necessary skills to engage in and profit from new technology and to manage the challenges that will reap the business opportunities that lie in disruptive technology (Assink, 2006).

Although prior case studies provide rich context for theory-building purposes, “*the most promising area for research would be to provide data specifying resources, processes, and values*” (Danneels, 2004; Karimi & Walter, 2015). Concerning this aspect, also Christensen highlighted three classes of factors that affect what an organization can or cannot accomplish: the **resources-processes-values (RPV)** framework. More in detail (Christensen, 1997):

- ***resources*** are the most visible of the factors that contribute to what an organization can and cannot do. They include people, equipment, technology, product designs, brands, information, cash,relationships with suppliers, distributors, and customers. Resources are usually things or assets and can be transferred across the boundaries of organizations much more easily than can processes and values.
- organizations create value by transforming inputs of resources—people, equipment, technology, product designs, brands, information, energy, and cash—into products and services of greater

worth. The interaction, coordination, communication, and decision-making activities through which they accomplish these transformations are ***processes***.

- ***values*** of an organization are the criteria by which decisions about priorities are made. An organization's values are the standards by which firms make prioritization decisions, at every level. At the executive tiers, they often take the form of decisions to invest or not invest in new products, services, and processes; among salespeople, they consist of on-the-spot, daily decisions about which products to push with customers and which not to emphasize; etc.

One of the management dilemmas is that, by their very nature, processes are established so that employees perform recurrent tasks in a consistent way, time after time. Indeed, to ensure consistency they are meant not to change - or if necessary, to change through tightly controlled procedures. From this it is possible to derive that "*the very mechanisms through which organizations create value are intrinsically inimical to change*" (Christensen, 1997).

Karimi & Walter (2015), given the lack of studies on the role of technology in enabling response to disruptive innovations, studied the topic of disruptive innovation focusing on technology managers, providing insights into key RPV factors that create first order dynamic capabilities (determinants) for responding to digital disruption in the Newspaper Industry. The authors identified the key constituents of RPV, through their specific dimension related to the industrial settings under investigation, that need to be changed, adapted or extended to create dynamic capabilities for managing innovation projects.

Introducing the next section focused on firm's capabilities and dynamic capabilities, with reference to high-velocity markets, this study seeks to identify which are the specific constituents of RPV in the digital manufacturing ecosystem that allow firms to create dynamic capabilities and achieve a competitive advantage.

2.3.3 Firm's Capabilities

The review of the literature on firm's capabilities developed in this section is divided in three parts: the first part presents a general overview of the literature on firm's capabilities. Next, since the purpose is to create strong foundations to define the concept of *digital manufacturing capabilities,* relevant literature concerning specific *manufacturing capabilities* is presented. Finally, the third part explores the theories of dynamic capability view (DCV) and resource-based view (RBV). The fundamental concepts of dynamic capabilities and the related organizational performances as well as competitive advantage are introduced and defined through the most significant literature existing in this field.

2.3.3.1 Initial Analysis of the Literature on Firm's Capabilities

Helfat and Winter (2011) concisely summarize the various definitions of organizational capability, noting that a capability is in place when "*the organization (or its constituent parts) has the capacity to perform a particular activity in a reliable and at least minimally satisfactory manner*" (Helfat & Winter, 2011).

Capability is the firm's physical ability to (re)act with speed to generate customer-driven products and services, which requires the exploitation of the competitive bases of efficiency, flexibility, innovation, and quality through the integration and reconfiguration of resources (Chen, 1996; Rai & Tang, 2010; Sambamurthy et al., 2003; Zaheer & Zaheer, 1997).

Furthermore, the term "capabilities" emphasises the key role of strategic management in appropriately adapting, integrating and reconfiguring organisational skills, resources and functional competencies to match the requirements of a changing environment. As will be analyzed more in detail in the next section, in high-velocity markets, the ability to renew competencies to accommodate the changing business environment is very important for firms, and in strategic management literature has been studied as dynamic capabilities (Assink, 2006; Teece et al., 1997).

Organizational ordinary capabilities are defined as "*high-level routine (or collection of routines) that, together with its implementing input flows, confers upon an organization's management a set of decision options for producing significant output of a particular type*" (Winter, 2003).

Previous studies suggest that firm's competitive capabilities are affected by both its internal and external resources.

Internally, competitive capabilities emerge through new uses or unexpected configurations of resources (Penrose, 1959) and through developing unique capabilities based on experiential learning (Helfat, 2000). Assink (2006) found that most large corporations lack the management ability to adapt the necessary skills to engage in and profit from new technology, and to manage the challenges that will reap the business opportunities that lie in disruptive technology innovation and highly dynamic context (Assink, 2006).

Externally, competitive capabilities are derived from a firm's network of partners (Ahuja, 2000; Kogut, 2000). By establishing interorganizational relationships, firms access external resources that provide complementary capabilities to discover opportunities and respond to the market with customer-driven offerings (Baum et al., 2000; Gulati, 1999). These resources that are embedded in partner relationships have emerged as an increasingly important source of a firm's capabilities to develop, sustain, and renew competitive advantage (McEvily & Marcus, 2005; Rai & Tang, 2010). For instance, a common way to exploit disruptive innovations is through initiating new business development (NBD) processes, throughout corporate "venturing", joint ventures, alliances, acquisitions, etc. However, some studies found out that many of these collaborations fail to generate breakthrough innovations because they focus on acquiring new products rather than new capabilities, lacking the ability to absorb knowledge by maximizing learning (Assink, 2006; Lynn et al., 1996; Powell, 1998).

The resource-based view promotes a distinction between resources and capabilities: capabilities reflect the ability of firms to combine resources in ways that promote superior performance (Amit and Schoemaker 1993). While firm resources are copied relatively easily by competition, capabilities are more difficult to replicate because they are tightly connected to the history, culture, and experience of the firm (Bharadwaj et al., 1999).

In order to be consistent with the previous paragraph, it is also important at this stage to provide a definition of *disruptive innovation capability*. Assink (2006), defined it as "The internal driving energy to generate and explore radical new ideas and concepts, to experiment with solutions for potential opportunity patterns detected in the market's white space and to develop them into marketable and effective innovations, leveraging internal and external resources and competencies" (Assink, 2006).

2.3.3.2 Manufacturing Capabilities

According to our topic of interest, this section explores in depth the literature on capabilities in the manufacturing context.

Hayes and Pisano (1996) argued that capabilities are *activities* that a firm can do better than its competitors. In addition, a capability is not something a firm can buy or exchange. Capabilities are organizationally specific; thus, they must be developed internally (Hayes & Pisano, 1996). The fact that they are difficult to imitate or transfer is what makes them valuable. Accordingly, capabilities derive less from specific technologies or manufacturing facilities and more from manufacturing infrastructure: people, learning, management and organizational focus.

Other researchers provided evidence that capabilities form the primary basis for *competition* between firms. It has been said that in the current business environment, the essence of strategy is to develop "*hard-to-imitate organizational capabilities that distinguish a company from its competitors in the eyes of its customers*" (Stalk et al., 1992). Core capabilities contained within a firm's manufacturing processes enable it to differentiate its products from competitors' products.

Core manufacturing capabilities are distinct from the notion of manufacturing *competence*, as defined by Vickery et al. (1993, 1994). From the prior discussion, we can see that manufacturing capability refers to a fundamental proficiency in manufacturing, whereas manufacturing competence can be described as the degree to which manufacturing performance supports the strategic objectives of the firm. Manufacturing competence therefore provides a measure, although an indirect one, of the extent of alignment between manufacturing capabilities and the competitive needs of the firm (Swink & Hegarty, 1998).

In this context, Großler and Grubner (2006) defined *strategic capabilities* as "*a plant's contribution to a company's success factors in competition, i.e. the strengths of a plant with which it wants to support corporate and marketing strategy and which help it to succeed in the marketplace*". The development, nurturing or arbitrary abandonment of strategic capabilities, constitute a main component of manufacturing strategy (Größler & Grübner, 2006)

According to Wheelwright (1984), *four main strategic capabilities* are commonly identified in manufacturing, as the ability to produce (Wheel Wright, 1984):

- With low cost;
- In high quality;
- With reliable and fast delivery;
- With flexibility, concerning mix and volume of products

Although other capabilities are discussed occasionally, for example, innovativeness or environmental soundness, and might be relevant in specific cases, the four capabilities of **cost, quality, delivery and flexibility** are seen to be the most important (Swink & Way, 1995; Ward et al., 1996; Ward et al., 1998; White, 1996). Therefore, the present study will consider them as the main (although not the exclusive) categories of firm's manufacturing capabilities.

Various authors have suggested many different manufacturing capabilities. Vickery et al. (1993) developed a comprehensive list of 31 "components of production competence" based on an extensive review of the literature. Only twelve items showed manufacturing responsibility greater than 30 % while all other items had manufacturing responsibility of 29.5% or less (see table below).

Item	**Manufacturing responsibility (%)**
Product flexibility	45.5
Volume flexibility	77.3
Process flexibility	74.4
Low product cost	62.5
Delivery speed	61.4
Delivery dependability	64.5
Production lead time	73.4
Product reliability	49.2
Product durability	51.0
Quality (conform to specs)	63.1
Competitive pricing	41.1
Low price	33.9

Several items on the preceding list are very similar and can be combined together under a common label (e.g. Low Price, Competitive Pricing and Low Production Cost under the manufacturing competitive capability of "*cost"*), according to the four main categories discussed above.

Some of these capabilities, such as quality and flexibility, have been recognized as multidimensional constructs. For instance, existing research has studied **quality** as a manufacturing capability through two dimensions: either *conformance quality* (Hill, 1994) - i.e. customer satisfaction and customer complaints - or *perceived quality*.

From previous empirical work (Ferdows & De Meyer, 1990; Noble, 1995), it can be assumed that improvements in quality capabilities serve as the base for all other capabilities. Indeed, when a plant is able to improve on the quality dimension, all other capabilities benefit from these improvements (Größler & Grübner, 2006).

Flexibility, likewise quality, has been recognized as a multidimensional construct. Hill (1994) lists 'demand increases' (i.e. *volume flexibility*) and 'product range' (i.e. *product flexibility*) as the only two flexibility-related order winners and qualifiers that are specific to manufacturing. Indeed, the great majority of existing research that measures flexibility as a manufacturing capability has examined either one or both of these dimensions.

Relationships among manufacturing capabilities and between these capabilities and *business performance* are discussed by White (1996). The model proposed in the paper ties each competitive capability to business performance through improved competitiveness (associated with increased market share) and cost reductions. The external competitive environment is shown as interacting with manufacturing capabilities to determine market share. The model presented, based on empirical evidence and theoretical arguments, proposes that relationships exist among competitive capabilities. It proposes that the most direct relationships between manufacturing capabilities and business performance are through decreased costs and, consequently, higher profitability, thus providing one possible explanation for the strong relationship between return on investment (ROI) and ROI growth. Furthermore, although this model emphasizes only the manufacturing function and does not explicitly indicate the effect of marketing on market share, it does not preclude that effect. Thus, this model shows that a company's performance on manufacturing capabilities will influence market share, which would also presumably be influenced by marketing (White, 1996). The Figure below (Fig.2.13) shows this model.

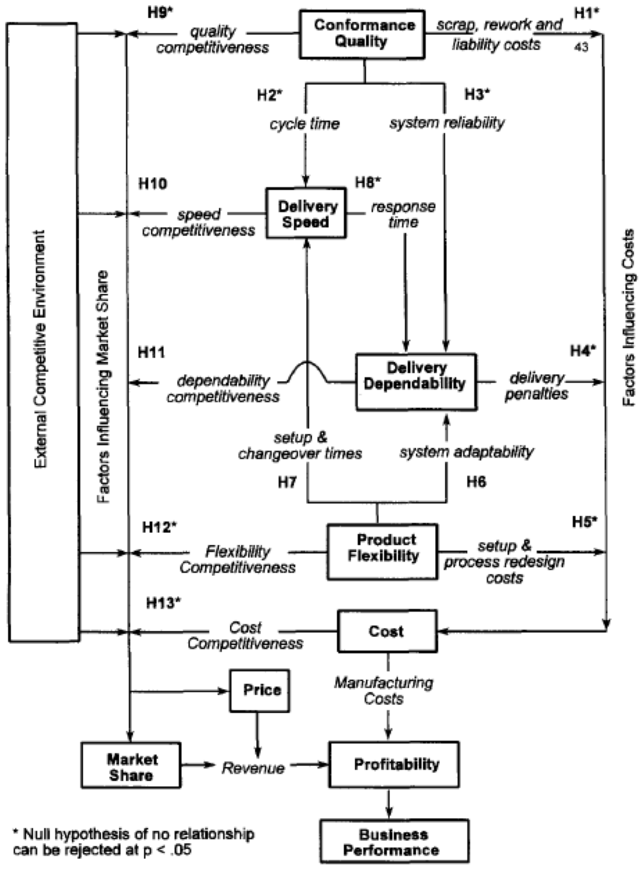


Fig.2.13. Model that links manufacturing capabilities and business performance (Source: White, 1996)

Cleveland et al. (1989), Roth and Miller (1992) and Vickery et al. (1993), provided evidence from cross-sectional survey studies to show that business performance is related to a company's performance on a set of four or more *competitive capabilities* (Cleveland, et al., 1989; Roth & Miller, 1992; Vickery et al., 1993).

Previously, Phillips et al. (1983) relied on the PIMS (Profit Impact of Market Strategies) database to test a model relating product quality to cost, market share and business performance (Buzzell & Gale, 1989; Phillips et al., 1983). Business performance was measured using the commonly accepted measure of ROI, while quality was measured in the PIMS database as perceived quality. Their results indicated that higher perceived quality was indeed related to higher market share and lower costs. They also found that higher market share and lower costs were also associated with higher ROI (White, 1996).

Further considerable literature concerning the relationship between manufacturing capabilities and performance (mainly in terms of performance gains) will be analyzed in depth on Chapter III, in order to define the construct of firm performance prior to its operationalization through the research instrument (see Section 3.2.3).

It is now crucial to understand through the literature what are the abilities that firms need in order to renew competencies and accommodate the changing business environment in high-velocity markets characterized by disruptive innovations and fast changes.

2.3.3.3 Dynamic Capabilities

The second research objective (RO2) requires to identify the antecedents necessary to develop firm-specific capabilities in order to take advantage of the digital manufacturing ecosystem dynamics. To achieve this goal, it is necessary to first define and explain the concept of *dynamic capability* as portrayed in the literature.

There is a broad consensus in the literature that “dynamic capabilities” contrast with ordinary (or operational) capabilities by being concerned with change (Winter, 2003). In his work Collins (1994) maintains that dynamic capabilities govern the rate of change of ordinary capabilities (Collis, 1994).

The term “dynamic” was used by Teece et al. (1997) - in their seminal article on dynamic capabilities approach – to describe “*situations where there is rapid change in technology and market forces, and ‘feedback’ effects on firms*”. Furthermore, the authors define competition among firms as a “*process involving the development, accumulation, combination, and protection of unique skills and capabilities*”, which are the foundations of a dynamic view of the business enterprise strategy to build up a long-run advantage and competitive flexibility (Teece et al., 1997).

With reference to the prior *resource-based approach* (or *resource-based view - RBV*) - which constitutes a theoretical underpinning of the dynamic capabilities approach - competitive advantage lies upstream of product markets, resting on the firm’s idiosyncratic and difficult-to-imitate resources (Teece, 1982). This highlights the importance of firm-specific factors in explaining firm performance. The theoretical framework of resource-based view of the firm seeks to understand how competitive advantage is achieved by firm and how that advantage might be sustained over time (Barney, 1991; Eisenhardt & Martin, 2000; Nelson, 1991; Penrose, 1959; Peteraf, 1993; Prahalad & Hamel, 1990; Schumpeter, 1934; Teece et al., 1997; Wernerfelt, 1984). More in detail, the RBV argues that firms possess resources, a subset of which enables them to achieve competitive advantage, and a further subset which leads to superior long-term performance (Barney 1991; Grant, 1991; Penrose 1959; Wade & Hulland, 2004; Wernerfelt 1984). Focusing on the internal organization of firms, this research stream is a complement to the traditional emphasis of strategy on industry structure and strategic positioning within that structure as the determinants of competitive advantage. Rumelt (1991) has shown that intra-industry differences in profits are greater than inter-industry, underlying the preponderance of firm-specific factors on industry effects (Rumelt, 1991). Thus, the resource-based perspective focuses on strategies for exploiting existing firm-specific assets, but also considers managerial strategies for developing new capabilities (Wernerfelt, 1984). Indeed, skill acquisition, learning, management of knowledge and know-how as well as accumulation of organizational and intangible or 'invisible' assets have important contributions to strategy (Itami & Roehl, 1991; Teece et al., 1997). Wade and Hulland (2004) have provided an overview of the RBV for its application in the IS Research. In their study, the authors extend the traditional static RBV conceptualization by making a distinction between stable and dynamic environments. Some resources are more useful to the firm in relatively stable environments (i.e. core resources), while others are more useful in dynamic, unstable, or volatile environments (i.e. dynamic resources). The concept of dynamic resources adopts a process approach: by acting as a buffer between core resources and the changing business environment, dynamic resources help a firm adjust its resource mix and thereby maintain the sustainability of the firm's competitive advantage, which otherwise might be quickly eroded (Wade & Hulland, 2004).

It is further crucial to understand what is exactly meant in literature by *resources* and *capabilities,* and how they are correlated together. Wade & Hulland (2004), by referring to extant literature (Sanchez et al., 1996), define *resources* "*as assets and capabilities that are available and useful in detecting and responding to market opportunities or threats*". Both assets and (substantive) capabilities describe the set of resources available to the firm. Assets are defined as anything tangible or intangible the firm can use in its processes for creating, producing, and/or offering its products (goods or services) to a market; capabilities are repeatable patterns of actions in the use of assets to create, produce, and offer products to a market and can include skills such as technical or managerial ability, or processes such as systems development or integration. Whereas assets can serve as tangible or intangible inputs to a process, capabilities transform inputs into outputs of greater value (Wade & Hulland, 2004).

As abovementioned, more recently scholars have extended the RBV to dynamic markets based on the rationale that this approach has not adequately explained how and why certain firms have competitive advantage in situations of rapid and unpredictable change (Eisenhardt and Martin, 2000). Indeed, the global competitions in highly technology-based industries have demonstrated the need for an expanded paradigm to understand how competitive advantage is achieved, since industry experts have observed that companies can accumulate large stock of valuable technology assets even without having many useful capabilities. In this scenario, Teece et al (1997) define *dynamic capabilities* as the "*ability to achieve new forms of competitive advantage*". More in detail, the term "*dynamic*" refers to "*the capacity to renew competences so as to achieve congruence with the changing business environment*", especially when "*time-to-market and timing are critical, the rate of technological change is rapid, and the nature of future competition and markets difficult to determine*". Furthermore, "*capabilities*" emphasize the "*key role of strategic management in appropriately adapting, integrating, and reconfiguring internal and external organizational skills, resources, and functional competences to match the requirements of a changing environment*". In addition, as noted by Bierly and Daly (2007), in "*high-technology industries, which have* *been referred to as hypercompetitive and high-velocity industries, the ability to frequently challenge the status quo with new, breakthrough ideas is critical for firm success*" (Bierly & Daly, 2007).

Innovating firms, in a Schumpeterian competition environment, need to identify difficult-to-imitate internal and external competences most likely to support valuable products and services. This choice about the domains of competence is influenced by past choices. Firms must follow a certain trajectory or path of competence development, which defines not only what choices are open today, but it also puts bounds around what firm's core competences are likely to be in the future. They represent the foundations upon which distinctive and difficult-to-replicate advantages can be built, maintained and enhanced over time (e.g. basis for diversification into new product markets) (Teece et al., 1997).

Similarly, Eisenhardt and Martin (2000) in their study to extend the understanding of dynamic capabilities, define them as consisting of "*specific strategic and organizational processes like product development, alliancing, and strategic decision making that create value for firms within dynamic markets by manipulating resources into new value-creating strategies*". More broadly, they see at D.C. as "*firm's processes that use resources—specifically the processes to integrate, reconfigure, gain and release resources—to match and even create market change. Dynamic capabilities thus are the organizational and strategic routines by which firms achieve new resource configurations as markets emerge, collide, split, evolve, and die*". Furthermore, the authors observe that these capabilities exhibit common features associated with effective processes across firms, described as commonalities or "best practice". They also note that effective patterns of dynamic capabilities vary with market dynamism: within moderately dynamic markets, where the change occurs in the context of stable industry structure, dynamic capabilities are similar to the traditional conception of routines; in contrast, in highly-velocity markets with blurring industry structures, dynamic capabilities rely on quickly created new knowledge and iterative execution to produce adaptive but unpredictable outcomes (Eisenhardt & Martin, 2000).

Accordingly, dynamic capabilities are the antecedent organizational and strategic routines by which managers alter their resource base - acquire and shed resources, integrate them together, and recombine them - to generate new value-creating strategies (Grant, 1996; Pisano, 1994).

Some dynamic capabilities integrate resources (i.e. product development routines), whereas others focus on the reconfiguration of resources within firms.

The capabilities of firms competing in the market are "*complex, structured and multidimensional*", and are present at different levels. Scholars have distinguished *dynamic* capabilities from *ordinary* ones. The hierarchical ordering of dynamic capabilities is a relevant nuance that informs the dynamic capabilities view (Fainshmidt, Pezeshkan, Lance Frazier, Nair, & Markowski, 2016). "Zero level" capabilities, also termed as ordinary or operational, allow firms to collect the revenues from its customers and buy more input in order make a living in the market. By contrast, capabilities that would change the product, the production process, the scale or the customers/markets served are configurable as dynamic capabilities. Thus, they alter *how* the firm makes its living. For instance, new product development is a prototypical example of *first-order* dynamic capability (Helfat & Winter, 2011; Winter, 2003). About this, Zahra et al. (2006) maintained that "*new routine for product development is a new substantive capability but the ability to change such capabilities is a dynamic capability*" (Zahra et al. 2006).

The first-order dynamic capabilities "extend, modify, change and/or create ordinary capabilities", affecting change in the resource base (Drnevich & Kriauciunas, 2011; Winter, 2003). In the absence of the firm's ability to create the first-order dynamic capabilities, ordinary capabilities and core competences - although very useful in the past - may become "*core rigidities*" or "*capability-rigidity paradoxes*" for future effective radical innovation (Johannessen et al., 2001; Leonard-Barton, 1992). A narrow orientation on, and use of, old competencies inhibits efforts to change capabilities (Assink, 2006; Levinthal & March, 1993).

If deploying first-order dynamic capabilities may not be sufficient, a firm may need to adapt its current approach or adopt a completely new approach to develop second-order dynamic capabilities. The *second-order (or higher-order)* dynamic capabilities, which result from organizational learning, enable spontaneous responsiveness in novel situations and modify or create lower order dynamic capabilities. (Karimi & Walter, 2015). Their nature entails change in the organization as a whole in order to harmonize with the environment. Moreover, higher-order dynamic capabilities generate value by facilitating more effective ad hoc problem solving. They influence performances both directly and indirectly, by enhancing lower order (i.e. first-order) dynamic capabilities (thus the effect of higher-order dynamic capabilities on firm performance is partially mediated by lower order dynamic capabilities).

Fainshmidt et al. (2016), in their meta-analysis across a large sample of studies and organizations, provided empirical evidence that dynamic capabilities have a positive impact on organizational performance (i.e. competitive advantage), supporting the notion that dynamic capabilities and performance are two related but distinct constructs. Furthermore, the authors considered another theoretical tenets within the DCV: dynamic capabilities are often argued to be more valuable in environments of rapid technological change (i.e. "technologically dynamic industries"). Altough several studies support this relationship (Drnevich & Kriauciunas, 2011; Helfat et al., 2007; Karimi & Walter, 2015; Schilke, 2014; Winter, 2003; Zahra et al., 2006; Zollo & Winter, 2002), Fainshmidt et al. (2016) - based on their meta-analysis results - suggested that technological dynamism may not be a significant moderator. Indeed, according to the authors, in these industries developing dynamic capabilities is key to stay in the race, but doesn't necessarily give firms a competitive advantage (Fainshmidt et al., 2016).

Table 2.20 presents, in chronological order, a sample of the most significant definitions of dynamic capabilities – considering the purposes of the present study - that have appeared in the literature to date.

Definition	Level of analysis	Source
Firm's ability to integrate, build, and reconfigure distinctive internal and external competences to address rapidly changing environments. Dynamic capabilities reflect an organization's ability to achieve new and innovative forms of competitive advantage given path dependencies and market positions.	Firm	*Teece et al., 1997*
Dynamic capabilities consist of specific strategic and organizational processes like product development, alliancing, and strategic decision making that create value for firms within dynamic markets by manipulating resources into new value-creating strategies. They are necessary but not sufficient for competitive advantage.	Firm	*Eisenhardt and Martin, 2000*
Dynamic resources act as a buffer between core resources and the changing business environment, helping a firm to adjust its resource mix and thereby maintain the sustainability of the firm's competitive advantage, which otherwise might be quickly eroded.	Firm	*Wade & Hulland, 2004*
Dynamic capabilities' contrast with ordinary (or 'operational') capabilities by being concerned with change. They govern the rate of change of ordinary capabilities.	Firm	*Winter, 2003*
The abilities to change or reconfigure a firm's resources and routines (existing substantive capabilities), in the manner envisioned and deemed appropriate by its principal decision-maker(s)	Entrepreneur/Manager	*Zahra et al., 2006*
Dynamic capabilities are the capacity of an organization to purposefully create, extend or modify its resource base	Firm	*Helfat et al., 2007*
Operational capabilities allow an organization to make a living in the present, while dynamic capabilities alter the way an organization currently makes its living	Firm	*Helfat & Winter, 2011*

Table 2.20. Dynamic Capabilities Definitions

For the purposes of this research, it is also crucial to investigate dynamic capabilities relevant to specific settings and processes. The identification of particular processes as dynamic capabilities has several implications. For one, it opens up RBV thinking to a large, substantive body of empirical research that has often been neglected within the paradigm. This research on capabilities such as product development and alliance formation sheds light not only on these specific processes, but also on the generalized nature of dynamic capabilities. So, contrary to the criticism that dynamic capabilities lack empirical grounding (Williamson, 1999), dynamic capabilities assessed as specific processes often have extensive empirical research bases and management applicability (Eisenhardt & Martin, 2000).

Based on previous definitions (see also table 2.20), this study considers DC as the *capacity of a firm to systematically create, extend and improve its specific resource base to achieve a competitive position in a fast changing economic context.*

Karimi and Walter (2015) analyzed the factors that create dynamic capabilities for responding to digital disruption in newspapers' companies. Recent research on how companies can transform themselves in response to disruptive innovations suggests that such transformation needs to happen as a result of two separate and simultaneous efforts (Karimi & Walter, 2015):

(1) Adapting the core business to the realities of the disrupted marketplace;
(2) Establishing a “capabilities exchange” that allows for a new disruptive business to create the next source of growth by sharing resources with the core business without interfering with it.

Furthermore, Cautela et al. (2014) studied the business model innovation process brought by design enterprises employing 3D Printing technologies, required for obtaining competitive advantage from this disruptive technology and transforming it into profits through the application of competencies and dynamic capabilities, as well as the ability to select and apply appropriate resources. Their empirical analysis suggests that 3-D printing technology allows both new design ventures and established prototyping companies to develop different distribution strategies. Direct e-commerce, alliances with established distributors, and specialized retail channels such as open design shops (i.e. FabLabs), turn collaborations between producers, distributors and customers into business competition. The open business model induces companies to achieve a profitable product portfolio through providing a wide variety of customized and low volume products with no technological complementarities, in which the management of the community prevails over the management of the brand. Moreover, 3-D printing ventures require dynamic capabilities related to network and market management, as well as project selection (Cautela et al., 2014).

Holmström et al (2016), in their research agenda paper concerning *direct digital manufacturing* in the Operations Management field maintain that DDM is a disruptive innovation that will revolutionize traditional manufacturing and its supply chains by leveraging its unique characteristics of enabling local high-variety manufacturing, providing setting to further develop theory on dynamic capabilities in digitalizing supply chains. Much exploratory work with early adopters remains to be done in order to understand what specific capabilities firms would need to compete in this environment (Holmström et al., 2016).

However, most prior Management and IS studies have not focused specifically on the role of both higher and lower-order dynamic capabilities in responding to digital disruption. Therefore, this research in the next chapters focuses on building the construct of *digital manufacturing capabilities,* and to understand their role in responding to the digital disruption that characterizes the manufacturing sector and achieving superior performance.

2.4 Chapter Summary

The literature review presented in this chapter had the purpose of establishing the theoretical foundations of this research. Since very little is known about the concept of digital manufacturing capabilities, it was necessary to review relevant literature on disruptive innovation, digital ecosystems, firm’s capabilities and dynamic capabilities.

The present literature review provided some fundamental insights and definitions to achieve the first two objectives set in Chapter 1:

RO1: develop a clear understanding of a firm's *Digital Manufacturing Capabilities (DMC)*; and

RO2: explore what are the factors that drive the development of a firm's DMC*.*

In addition, it allowed the identification of a number of theoretical concepts that are fundamental for the development of a conceptual model for this phenomenon.

Chapter 3 presents the conceptual research model together with the associated hypotheses, based on this literature review.

3. Chapter III: Conceptual Model and Research Hypotheses

This chapter describes the development of the conceptual research model and research hypotheses used to guide this investigation. Initially, the research model presented in Chapter 1 is revisited. This is followed by an in-depth discussion of each construct as well as the development of the research hypotheses.

3.1 Conceptual Research Model

As outlined in the literature review (Chapter 2), this study builds on disruptive innovation theory and DCV by ascertaining the effect of dynamic capabilities on the performance obtained in response to the digital disruption of the manufacturing process.

Previous research suggests through empirical results that dynamic capabilities - that are created by systematically changing, extending, or adapting a firms existing resources, processes, and values - are positively associated with building firm specific capabilities connected to the context in which they operate (i.e. digital manufacturing capabilities), and that these capabilities impact firm performance in responding to digital disruption (Fainshmidt et al., 2016; Karimi & Walter, 2015; Kim et al., 2013). Indeed, organizational ordinary and dynamic capabilities have been shown to influence performance at firm and process levels through various mechanisms.

This section brings together the topics previously discussed in the literature review and explains the conceptual model for this research.

Models are simplified representations of phenomena (i.e. the existence of things) reflecting key features of the world that are important to a researcher. Models are made up of constructs that are representations of a group of things as opposed to a particular attribute of a specific thing. Hypotheses are the expected associations and relationships between these constructs. Many associations could occur, however not everyone of these is represented in a model as researchers decide on which ones to include and which to eliminate based on their views (Creswell, 2014; Weber, 2012).

Because of the relatively new phenomenon under investigation and the exploratory nature of the study, this research presents a conceptualisation of the phenomena to begin with. Key themes from the literature review were used for the development of the conceptual research model (see Figure 3.1).

The present theoretical model investigates:

1. The direct effects of the higher-order dynamic capabilities on firm performance in response to digital disruption;
2. The role of these capabilities in building digital manufacturing capabilities;
3. The mediating role of digital manufacturing capabilities on the impact of higher-order dynamic capabilities on firm performance in response to digital disruption.

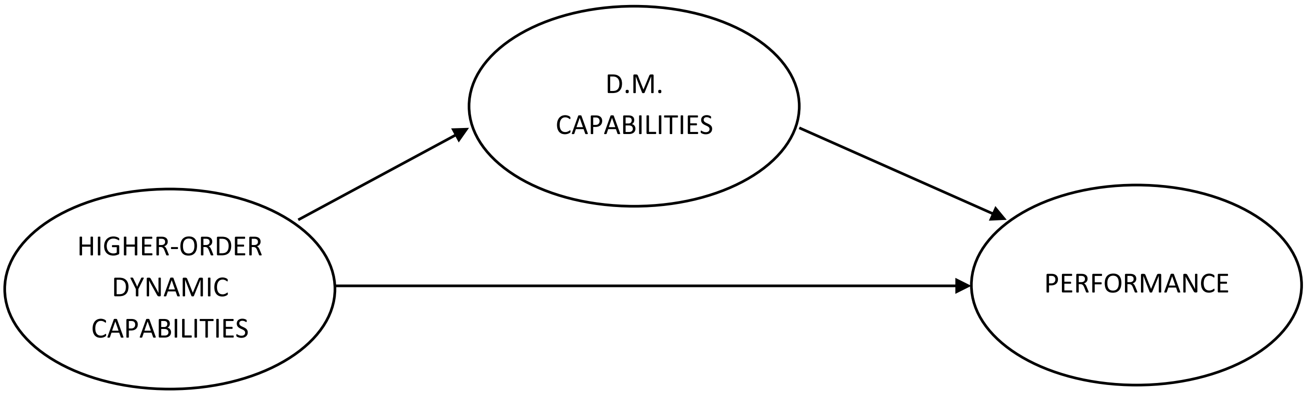


Fig.3.1. Conceptual Research Model

The model is composed of three key elements (constructs):

- The construct of *Higher-Order Dynamic Capabilities* (HODC)
- The construct of *Digital Manufacturing Capabilities* (DMC), which is the central point of this research and will be explained in the following section (configured as the mediator)
- The construct of *Firm Performance* (PERFORMANCE), that this research considers both as its own internal performance compared over a period of time as well as firm's competitive advantage on the marketplace-industrial level of analysis.

In the following sections, the abovementioned constructs are defined with reference to the literature analyzed in the previous chapter, and relevant hypotheses concerning the relationships among them are developed.

3.2 Variables and Research Hypothesis

In this section the research model is further defined. The model considers the role of each variable and its reference to the literature. Then, the expected relationships between variables are stated in the form of research hypotheses.

It is important to note that this research has its foundations in the studies of Karimi & Walter (2015) and Fainshmidt et al. (2016), taking their frameworks as reference points for further empirical investigation.

3.2.1 Higher Order Dynamic Capabilities

As illustrated in the literature review (see section 2.3.3.3), in dynamic environments (referred to as "rapidly changing environments") where "there is rapid change in technology and market forces, and 'feedback' effects”, a firm’s core resources (also defined as “ordinary”, “operational” or “zero level” capabilities) allow the firm to earn a living in the present but are not sufficient to achieve superior performance and obtain a competitive advantage in the market (Teece et al., 1997; Wade & Hulland, 2004). In these contexts of “rapid and unpredictable change”, often characterized by disruptive innovation, firms need to frequently challenge the status quo by manipulating and reconfiguring resources into new value-creating strategies (Bierly & Daly, 2007; Eisenhardt & Martin; 2000). These abilities to change firm routine and substantive capabilities have been defined in literature as *dynamic capabilities.*

At this point it is important to note that whereas (*first or) lower-order dynamic capabilities* extend, modify, change and/or create ordinary capabilities”, (*second or) higher-order dynamic capabilities* - resulting from organizational learning - entail change in the organization as a whole in order to harmonize with the environment (Drnevich & Kriauciunas, 2011; Winter, 2003). Higher-order dynamic capabilities are more fungible, may lead to improved ad hoc problem-solving within organizations, and are more likely to allow organizations to initiate path-breaking changes in their environment (Schilke, 2014; Teece, 2014). Higher order dynamic capabilities generate and positively affect lower-order dynamic capabilities as well as performance (Fainshmidt et al., 2016; Hult & Ketchen, 2001; Karimi & Walter, 2015).

Therefore, based on the analyzed theoretical frameworks of Resource Based View (RBV) and Dynamic Capabilities View (DCV), *Higher-Order Dynamic Capabilities* can be understood as the capacity of a firm to systematically create, extend and improve its specific resource base to achieve a competitive position in a fast changing economic context (Ambrosini & Bowman, 2009; Assink, 2006; Barney 1991; Bierly & Daly, 2007; Eisenhardt and Martin, 2000; Fainshmidt et al., 2016; Grant 1991; Helfat et al., 2007; Helfat & Winter, 2011; Penrose 1959; Peteraf, 1993; Prahalad & Hamel, 1990; Rumelt 1991; Schilke, 2014; Teece et al., 1997; Teece, 2014; Wade & Hulland, 2004; Winter, 2003; Zahra et al., 2006).

Consistently with the literature review and our research questions and objectives, in this study the construct of **Higher-Order Dynamic Capabilities** is defined as the *capacity of a firm to systematically change its specific resource base in terms of resources-processes-values (RPV) to improve its competitive position in a fast changing economic context.*

As empirical results from the meta-analysis carried out by Fainshmidt et al. (2016) (see figure 3.2 below), higher-order dynamic capabilities generate value - i.e. contribute to organizational performance - both directly and indirectly by enhancing lower-order dynamic capabilities (that in our model are represented by digital manufacturing capabilities - DMC).

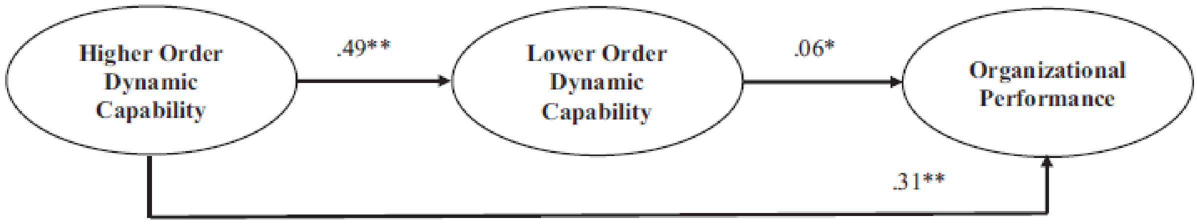


Fig. 3.2. Relationship Among Different Orders of Dynamic Capabilities and Organizational Performance (Source: Fainshmidt et al., 2016)

As a result of these evidences from the literature, Hypothesis 1 is formulated:

H1: Higher-order dynamic capabilities have a positive direct effect on firm performance.

3.2.2 Digital Manufacturing Capabilities

Winter (2003) defined lower-order dynamic capabilities as those capabilities affecting change in the firm resource base or firm ordinary capabilities. Thus, capabilities that would change the production process, the product (i.e. new product development), the scale, or the customers (markets) served are prototypical examples of first or lower-order dynamic capabilities (Winter, 2003).
According to this description, and consistent with the literature reviewed in section 2.3.3 et seq., it is possible to define *digital manufacturing capabilities* as lower-order dynamic capabilities.

In addition, the findings of qualitative research (i.e. Athreye, 2005; Brady & Davies, 2004; Clark & Fujimoto, 1991; Figueiredo, 2003; Petroni, 1998; Wang & Ahmed, 2007; Woiceshyn & Daellenbach, 2005) point out that capability development seems to be a mediator of the higher-order dynamic capabilities and performance relationship. Theoretical development also supports such indirect connections: dynamic capabilities create and shape a firm's resource position (Eisenhardt & Martin, 2000; Galunic & Eisenhardt, 2001) and capabilities (Kogut & Zander, 1992), which in turn determine the firm's product–market position and, consequently, its performance (Wang & Ahmed, 2007; Zott, 2003).

Indeed, *digital manufacturing capabilities* refer to the extent to which manufacturers reconfigure their distinctive operational capabilities (i.e. manufacturing capabilities) and resources in order to meet the competitive needs of the firm, in response to the digital transformation of the ecosystem brought by the disruptive technological innovation (Assink, 2006; Bharadwaj et al., 1999; Chen, 1996; Größler & Grübner, 2006; Hayes and Pisano 1996; Porter & Heppelmann, 2014, 2015; Rai & Tang, 2010; Sambamurthy et al. 2003; Sarmiento et al., 2010; Swink and Hegarty, 1998; Wheel Wright, 1984; Zaheer and Zaheer 1997).

Consistently with the literature reviewed and analyzed as well as our research questions and objectives, in this study the construct of **Digital Manufacturing Capabilities** is defined as *the extent to which* *manufacturers use digital disruptive technological innovation to reconfigure their distinctive operational capabilities and resources (i.e. enhancing the design/development, manufacturing and features of their products), in order to meet the competitive needs of the firm.*

Consequently, Hypothesis 2 is formulated:

> **H2:** Higher-order dynamic capabilities generate and positively influence digital manufacturing capabilities**.**

This second hypothesis describes the extent to which the systematic change and reconfiguration of internal resources and competences effectively drives the development and adoption of new digital manufacturing resources and skills, enhancing firm strategic manufacturing capabilities.

In addition and consistent with the reasoning provided in the previous paragraphs, the development of DMC in turn contributes to generate value by significantly impacting organizational performance. Therefore, Hypothesis 3 is generated:

> **H3:** Digital manufacturing capabilities have a positive influence on performance**.**

Finally, supported by the literature reviewed, it is possible to hypothesize that digital manufacturing capabilities mediates the relationship between higher-order dynamic capabilities and firm performance (Fainshmidt et al. 2016; Karimi & Walter, 2015; Winter, 2003). As a result, the last hypothesis of this study is elaborated:

> **H4:** The impact of higher-order dynamic capabilities on performance is partially mediated by the extent to which a firm develops digital manufacturing capabilities.

Given these last two hypotheses, it is now important to define the construct of firm performance.

3.2.3 Performance

Finally, it is necessary to define the construct that describes and evaluates firm performance and its modifications due to the development of higher-order dynamic capabilities and new specific digital manufacturing capabilities.

As previously observed, literature about dynamic capabilities confirmed both a direct and indirect relationship between these capabilities and firm performance, often describing them as a source of competitive advantage (Ambrosini & Bowman, 2009; Bowman & Ambrosini, 2003; Griffith & Harvey, 2001;

Lee, Lee, & Rho, 2002; Priem & Butler, 2001; Teece *et al.* 1997; Zott, 2003). In particular, while the literature presents also evidence that dynamic capabilities "*do not necessarily lead to competitive advantage*" (Helfat et al., 2007), in the majority of the cases this positive connection is recognized (Fainshmidt et al., 2016; Karimi & walter, 2015; Pezeshkan et al., 2016).

More in detail, Ambrosini and Bowman (2009) found in the literature four different outcomes resulting from the deployment of dynamic capabilities:

- They can lead to *sustainable competitive advantage* if the resulting resource base is not imitated for a long time and the rents are sustained;
- They may lead to *temporary advantage*. Particularly, in "hypercompetitive environments, competitive advantage is transient rather than sustainable", competitive advantage can only be enjoyed for a short period of time (Rindova & Kotha, 2001);
- They can only give *competitive parity* if their effect on the resource base simply allows the firm to operate in the industry rather than to outperform rival firms;
- They may lead to *failure* if the resulting resource stock is irrelevant to the market.

By referring specifically to manufacturing performance and taking into account the three main theoretical frameworks of **Trade-off** (Skinner 1969, 1974, 1996), **Cumulative capabilities** (Ferdows and de Meyer 1990; Nakane 1986; Noble 1995; Wacker 1996) and **Rigid-flexibility** (Collins and Schmenner, 1993) models, Sarmiento et al. (2010) noted that performance measures should be observed and measured within an *industry-level analysis* as well as at the "*internal improvement*" organizational level of analysis. Indeed, according to Skinner's trade-off model, studies on this topic should incorporate manufacturing performance measures that reflect the status of an organization compared to its competitors (e.g., industry, marketplace, etc.) (Sarmiento et al., 2010).

The three models cited above offer varying views on how a manufacturing organization can achieve performance levels that can provide it with a competitive advantage in the industry. There is some evidence showing that by successfully implementing advanced manufacturing technologies (e.g., TQM, JIT, lean manufacturing, etc.) a firm is able to achieve high levels of performance on two or more manufacturing capabilities. At the same time, Skinner argues that no manufacturing system can achieve high levels of performance across all manufacturing capabilities, since any system is delimited by its technologies of equipment, processes, materials and management (Skinner, 1996).
Thus, Sarmiento et al. (2010) highlighted some issues that need to be explored in this context:

- The two types of Organizational performance assessments/comparisons - internal (i.e., changes in performance over time) and external (against industry and competition levels), should be clearly distinguished from each other.

- There should be a method by which these two levels of performance assessments should be measured.
- These two levels of performance assessments should be made for each strategic performance criteria dimension (e.g., quality, delivery, flexibility, costs, revenues, market share, etc.).

In addition to what already discussed, also Wang & Ahmed (2007) focused on a firms' ability to attain and sustain competitive advantage. The authors analyzed the path-dependent nature of dynamic capabilities and their impact on long-term performance, which can be measured by the firm's key (both *market and financial*) performance indicators in comparison with its main competitors or the industry average over a period of five to ten years. They also noted that the relationship between dynamic capabilities and firm performance is more complex than a simple, direct effect. Indeed, dynamic capabilities are "*conducive to long-term firm performance, but the relationship is an indirect one mediated by capability development which, in turn, is mediated by firm strategy; dynamic capabilities are more likely to lead to better firm performance when particular capabilities are developed in line with the firm's strategic choice*" (Wang & Ahmed, 2007).

More recently, Laaksonen and Peltoniemi (2016) argued that since the purpose of dynamic capabilities research is to explain sources of competitive advantage (David J. Teece, 2007; Teece et al. 1997), firm performance is a key component of the theory and is usually seen as the ultimate aim of dynamic capabilities. Competitive advantage is achieved when a firm enjoys a superior success than current or potential competitors in its industry (Peteraf and Barney, 2003). Dynamic capabilities change ordinary capabilities or the firm's broader resource base, and this change may finally cause a change in performance. Therefore, dynamic capabilities cannot explain the performance itself, but rather changes occurred in performance (Laaksonen & Peltoniemi, 2016).

Finally, Fainshmidt et al. (2016) in their paper adopted several types of performance indicators, in the form of coded dummy variables: *strategic* (i.e., competitive advantage), *financial, operational, innovation,* and *growth*.

Given what has been said so far, in this study the construct of performance will be understood as the *internal (performance gains overtime) and external (competitive advantage measured at industry level) outcome a firm can obtain by dynamically responding to the contextual change (in the manufacturing sector) through the development of new capabilities and resources, based on managers' evaluations.*

3.3 Chapter Summary

This chapter outlined the development of the research model that guides this investigation. Initially, the refined research model was briefly introduced (Figure 3.1). This was followed by an in-depth discussion of each construct as well as the development of the associated research hypotheses (summarized below on Figure 3.3). In addition, the research model is proposed again below with the representation of the 4 main hypotheses (see fig. 3.3).

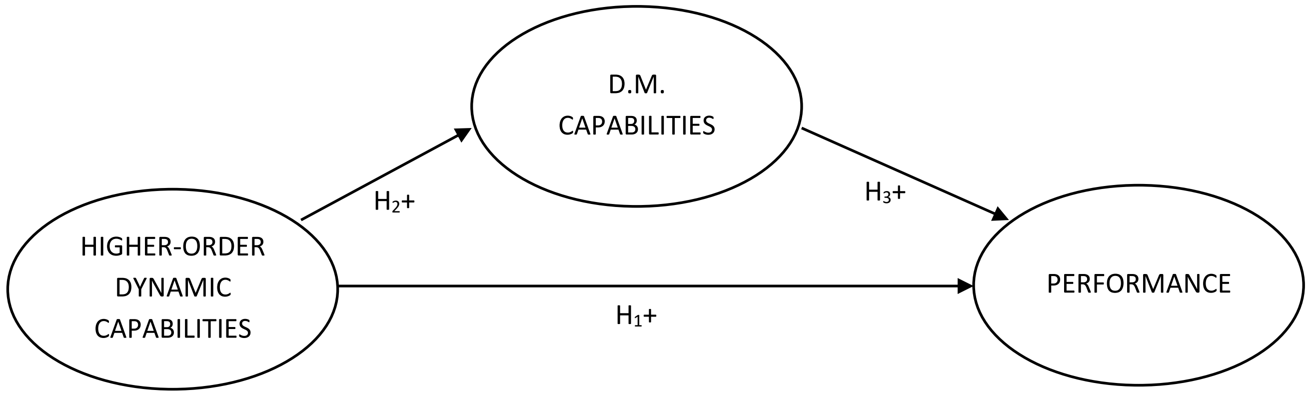


Fig.3.3. Conceptual Research Model with Relevant Hypotheses

H1: Higher-order dynamic capabilities have a positive direct effect on firm performance.

H2: Higher-order dynamic capabilities generate and positively influence digital manufacturing capabilities**.**

H3: Digital manufacturing capabilities have a positive influence on performance.

H4: The impact of higher-order dynamic capabilities on performance is partially mediated by the extent to which a firm develops digital manufacturing capabilities.

Given these hypotheses, the conceptual research model is configured as a mediation model (characterized by *partial mediation*) – or intervening variable model – in which a variable X (HODC) is postulated to exert an effect on an outcome variable Y (Performance), through one intervening variable, also called "mediator" (DMC) (Hayes, 2009).

4. Chapter IV: Research Design and Methodology

4.1 Introduction

Following the development of the conceptual model and the establishment of the research hypotheses, this chapter outlines and explains the methodological considerations on which this study is structured. Thus, the purpose of this chapter is to explain the research design, which provides a general framework for the work. In turn, the initial research question provides an early direction for the research design (Scornavacca, 2010).

The chapter starts with a discussion that identifies the selected research paradigm and the philosophical approach undertaken. The research paradigm then guides the development of the research methodology. Finally, the research design describes the strategy used to meet the research objectives (RO1, RO2 and RO3) and to answer the research question.

4.2 Research Paradigm

Scientific research can be generally defined as a *creative discovery process developed according to a predetermined itinerary and following established procedures that have been consolidated within the scientific community* (Corbetta, 1999). It is an activity that contributes to the understanding of a phenomenon (Kuhn, 1996; Lakatos, 1978).

Research paradigms are philosophical assumptions researchers bring to the study. Specifically, they are general philosophical orientation about the world and the nature of research (Creswell, 2014).

Any research project consists of several underlying assumptions about what constitutes 'valid' research and which research methods are appropriate (Myers, 1997). In general, social research has the purpose of exploring, describing and/or explaining a phenomenon (Babbie, 1990; Hirschheim, 1992; Babbie, 2012; Myers 1997; Creswell 2003). Each purpose has different implications with regards to the adoption of a research approach as well as in the different aspects of the research design (Babbie, 2012; Benbasat and Weber 1996).

As illustrated by the research model in Chapter 3, the current research has the purpose of explaining a phenomenon (Babbie, 2012; Straub et al. 2004). Indeed, as will be further explained in the next section, the first exploratory-qualitative phase just served to explore and better understand the phenomenon of interest by collecting some insights through empirical cases. It represented a preliminary phase based on which it was possible to refine the literature analysis/review and build up the current predictive research model that will be tested in the quantitative phase. Therefore, the research described in the following chapters actually starts from the adoption of the aforementioned existing theories and relationships among variables, adapted to the phenomenon of interest from reference disciplines, that will be tested in order to explain the latter phenomenon and verify the hypotheses developed. Thus, following the deterministic philosophy underpinning the positivist tradition, the problem is studied to identify and assess the causes that influence outcomes (i.e. antecedents and consequences) by developing numeric measures of observations and studying behaviour and perceptions of the individuals. Positivist assumptions have represented the traditional form of research, holding more for quantitative than qualitative approaches. This epistemology is sometimes mentioned as the "scientific method", empirical science or postpositivism. Postpositivism represents the thinking after positivism, challenging the traditional notion of the absolute truth of knowledge and recognizing that it is not possible to be positive about our claims of knowledge when studying the behaviour and actions of humans (Creswell, 2014; Phillips & Burbules, 2000).

In their work Orlikowski and Baroudi (1991) described the nature of positivist studies as follows: *"Positivist studies are premised on the existence of a priori fixed relationships within phenomena which are typically investigated with structured instrumentation. Such studies serve primarily to test theory, in an attempt to increase predictive understand of phenomena"* (Orlikowski & Baroudi, 1991).
Accordingly, this research adopts a positivist epistemology since it (Orlikowski & Baroudi 1991; Babbie, 2012; Myers, 1997; Mingers, 2003):

i. assumes that reality is objectively given – i.e. it exists "out there" in the world - and can be described by measurable properties which are independent of the observer;
ii. examines causal relationships; and
iii. attempts to test theory, in an endeavor to increase the predictive understanding of phenomena.

4.3 Research Approach and Methodology

The *research outline* is a schematic form, which facilitates the researcher to have a logical order to the work. Pinsonneault and Kraemer (1993) considered that the research outline is a strategy used to refine and answer the research questions as well as to test the hypotheses which inspired the research.
Figure 4.1 presents the research outline that guided this work. As shown in the figure below, the research was divided into three phases. The first phase consisted of a preliminary exploratory stage to the research with the purpose of gaining a clearer picture of the phenomenon of interest. It is presented in this chapter (next section analyzes its results), and it can be considered as an antecedent phase to the research process described in this thesis. The second phase is constituted by the Research Model design and refinement (already discussed in Chapters 1, 2 and 3), and includes the development of the research instrument (described thoroughly in Chapter 5). The third part is focused on the test of the theoretical model, which is presented in detail in Chapter 6.

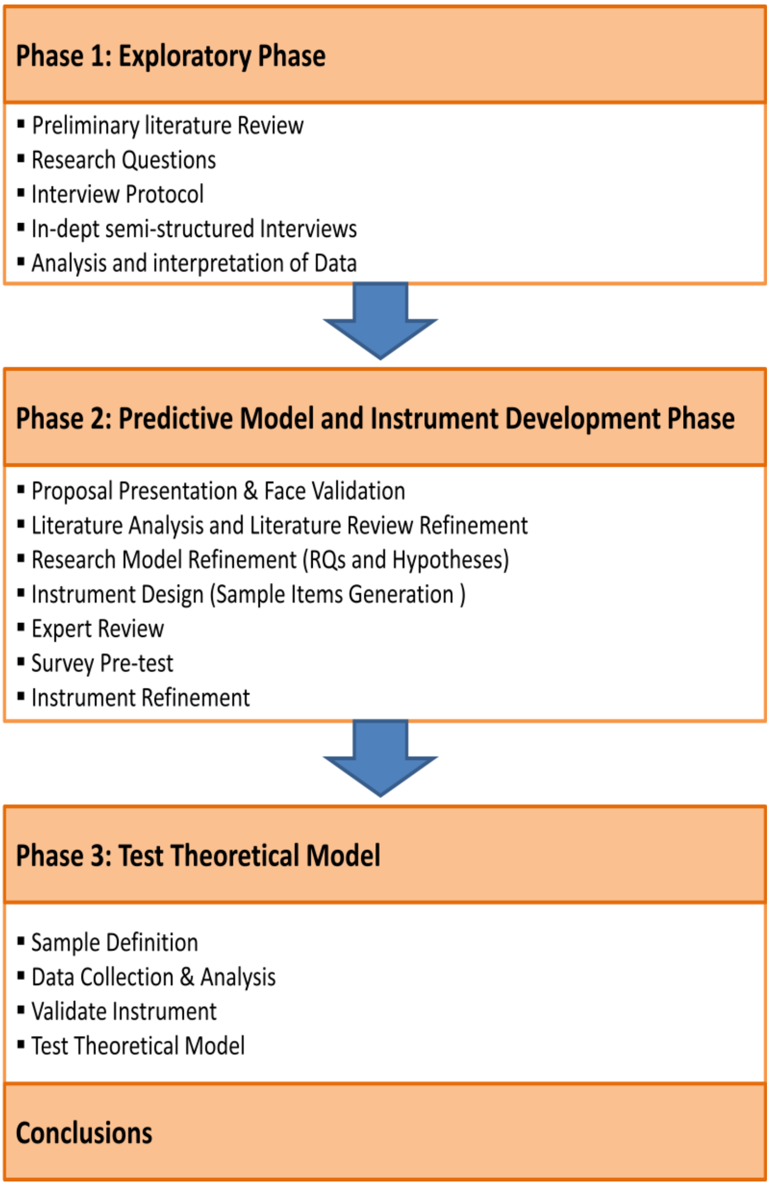


Fig. 4.1. Research Outline

The *research approach* represents the plan to conduct research, involving the intersection of philosophy (represented by the abovementioned research paradigm), the type of research strategy used (i.e. research design) and specific methods employed in conducting these strategies .

To explore the Digital Manufacturing Ecosystem phenomenon, a sequential mixed methods approach was configured; thus results from each phase fed into the later one (Mingers, 2001). Particularly, this research presents an *exploratory sequential mixed methods* approach, as the phenomena of interest required qualitative data prior to the creation of a predictive model, which is then tested through a quantitative manner (Creswell, 2012) – aligned with using both inductive and deductive empiricism. *"An exploratory sequential mixed methods is a design in which the researcher first begins by exploring with qualitative data and analysis and then uses the findings in a second quantitative phase"*. The combination of both qualitative and quantitative methods allows for validation of findings and for the corroboration of results

by comparing multiple sources of data. This combination provides a more complete understanding of the research problem than either approach alone (Creswell, 2014). Indeed, this research employs a three-phase procedure with the first phase being purely exploratory, the second represented by model design and refinement (creation of research hypotheses) and instrument development (i.e. questionnaire), and the third as administering the questionnaire to a sample of a population for testing the theoretical model.
The first phase is exploratory of nature since it investigates an idea in order to understand more about it. It assesses the research phenomena from a new angle, trying to identify the theoretical perspectives to be adopted and using new ways to measure the phenomena (Johnson et al., 2007; Kaplan & Duchon, 1988; Mingers, 2001; Venkatesh et al., 2013). In the next paragraph the research framework will be described in all its phases following the representation provided below (see Fig. 4.2):

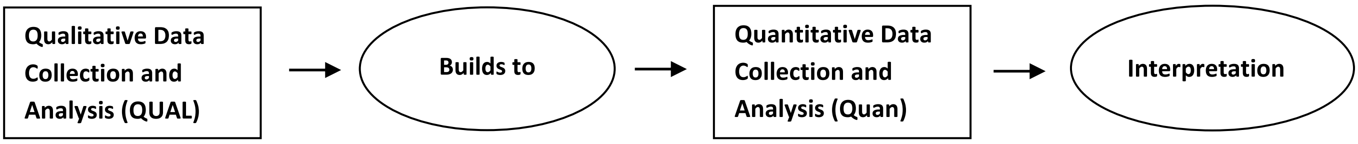


Fig.4.2. Research Design Representation (Source: our adaptation from Creswell, 2014)

Research Methods and Procedures:

- <u>Qualitative phase</u> (exploratory): employs a *multiple-case study* design (Stake, 1995; Yin, 2008; 2012) based on in-depth face to face interviews (with managers from the industry as well as from the consulting business, all operating in the manufacturing sector) following semi-structured guideline with open-ended questions.

  As previous literature demonstrated, the distinctive need for case studies arises out of the desire to understand complex social phenomena (Yin, 2003). Building theories from case studies is a research strategy that involves using one or more cases to build theoretical constructs, propositions and/or midrange theories from case-based, empirical evidence (Eisenhardt, 1989). They are rich, empirical descriptions of particular instances of a phenomenon that are typically based on a variety of data sources (Yin, 1994).

  Case studies are mainly used as the basis from which a theory can be developed inductively. The theory emerges from a practical case and is developed by recognizing patterns of relationships in constructs and cases. The use of an inductive theory building approach from cases is relevant especially in the first stage of an analysis, because it can produce new theories that are accurate, interesting and testable or provide important insights for advancing the knowledge about an emerging topic. In addition, as Eisenhardt and Graebner (2007) highlighted, studies that use multiple cases instead a single case can delineate constructs and relationships more precisely because it is easier to determine accurate definitions and appropriate levels of construct abstraction (Eisenhardt & Graebner, 2007). Therefore, theory building from multiple cases typically yields more robust, generalizable, and testable theories than single-case research (Cautela et al., 2014; Rieple & Pisano, 2015; Yin, 2003).

In-depth interviews with managers from different industries of the manufacturing sector were carried out in order to gain important insights to understand the phenomenon under investigation by obtaining a direct testimony from those who work daily in this environment. Particularly, this phase is used to recognize themes/patterns and specify variables which need to go into a follow-up quantitative phase, after having identified a robust theoretical lenses for creating the research model. Indeed, the interpretation of themes and patterns emerged from data can represent the basis to identify appropriate theoretical frameworks (by reviewing reference disciplines) and instruments (i.e. scales and questionnaires) or to develop new variables, for investigating the problem of interest in the subsequent phases. Results from initial data gathering methods facilitate upcoming methods of data gathering (Bryman, 2008).

- <u>Model Refinement and Instrument Development phase</u>: The reason for this refinement step is to update, validate and confirm the research model prior to testing it in the third, quantitative phase of the research. Evidences from the prior phase made possible to find more clearly an existing theory from the literature suitable to be adopted as a framework for studying the present emerging phenomenon of interest.

  This phase consists of a combination of academic/expert reviews and the refinement of the theoretical background (through a literature analysis and review). In particular, before initiating this second phase of the research, specific precautionary steps were taken: first, a formal research proposal was submitted to the Management Department of Sapienza University; subsequently, the same research proposal was presented at the official *Doctoral Consortium of the 13th International Conference of the Italian Chapter of AIS* (Association for Information Systems[1]), which took place at the University of Verona (Santa Marta campus) on October 7 – 8, 2016. Afterwards, for a face validity, the conceptual model was scrutinized by a pool of specialists (senior professors from Sapienza University of Rome and University of Baltimore) as well as managers specialized in Digital Transformation operating in the Manufacturing Sector (Creswell, 2003). The feedback received during these phases generated the need for a refinement of the literature review, as well as for further data gathering to clarify and confirm the concepts under investigation.

[1] http://aisnet.org/

Collectively, the qualitative phase and the model refinement phase allowed to transform the updated conceptual research model into the actual testable form (presented in Chapter 3).

- <u>Quantitative phase (follow-up)</u>: Correlational design (non-experimental form), uses correlational statistics to describe and measure the degree of association among two or more variables or a set of scores (Creswell, 2012).

  Concretely, this phase consists of a web-based Survey Research with enterprises - managers and senior executives from the industry as well as from the consulting business - built on a questionnaire implemented on the base of the results achieved at the end of the previous phases. Questionnaire items and scales have been developed according to the hypotheses, relying on the refined literature review and based on the adaptation of existing theoretical frameworks (i.e. DCV, RBV and RPV, already analyzed in chapter II), validated questionnaires from the literature and on the creation of completely new constructs (i.e. Digital Manufacturing Capabilities).

  Entirely different samples have been used for the qualitative and the quantitative components of the study. Indeed, a good procedure is to draw both samples from the same population (i.e. enterprises and consulting businesses operating in the manufacturing sector) but make sure that the individuals for both samples are not the same. To involve individuals in help developing the instrument and then to survey them in the quantitative phase would introduce confounding factors into the study.

  The collected data will then be statistically analyzed through the technique of Structural Equation Modeling (PLS-SEM), with the intent of testing the hypothesized relationships among variables, and possibly generalizing evidences from a sample to a population (Creswell, 2014; Fowler, 2009). Methods for data collection and analysis will be described more in detail in section 4.6.

  As per the two different samples selections, in the interpretation of the results it does not make sense to compare the qualitative and the quantitative databases. Indeed, they are drawn from different samples, and the intent of the strategy is to determine if the variables selected after the model refinement are reliable and representative of a larger population.

4.4 Preliminary Exploratory Phase Results

This research project starts from the evidences resulting from a number of past qualitative researches, that we carried out in the form of Multiple-case study focused on the main topic, recently published as book chapters or conference proceedings:

1. Savastano, M., Amendola, C., D'Ascenzo, F., Massaroni, E. (2015): 3-D Printing in the Spare Parts Supply Chain: an Explorative Study in the Automotive Industry. *Digitally Supported Innovation in Theory and Applied Practice. A Multi-Disciplinary View on Enterprise-, Public Sector- and User-Innovation, Lecture Notes in Information Systems and Organisation, Springer.*

2. Savastano, M., Bellini, F., D'Ascenzo, F. (2016): FabLab And Digital Manufacturing: Innovative Tools For The Social Innovation And Value Co-Creation. *The social relevance of the Organisation of Information Systems and ICT, Lecture Notes in Information Systems and Organisation, Springer.*

3. Savastano, M., Amendola, C., D'Ascenzo, F. (2016): Additive Manufacturing e Stampa 3D: Stato dell'arte e Opportunità per una Gestione Sostenibile della Supply Chain. *Supply Chain Sostenibile: Aspetti Teorici ed Evidenze Empiriche*. Cedam.

4. Savastano, M., Amendola, C., D'Ascenzo, F. (2016): How Digital Transformation is Reshaping the Manufacturing Industry Value Chain: The New Digital Manufacturing Ecosystem Applied to a Case Study from the Food Industry. *Proceedings of the ItAIS Conference (2016)*.

In these studies we investigated different strategies and degrees of implementation of the digital manufacturing ecosystem within SMEs, big industrial groups (i.e. Mercedes-Benz and Barilla Group) and FabLabs (i.e. BIC Lazio and Roma Makers FabLabs). In this context *FabLabs – i.e.* fabrication laboratories, originated by a project of Prof. Neil Gershenfeld at the Massachusetts Institute of Technology in Boston (MIT Center for Bits and Atoms, established in 2001) – have the role of platforms for the dissemination of digital knowledge through the collaborative development and sharing of skills, tools, ideas and projects.

In particular, face-to-face interviews (which last more than an hour each) were based on a semi-structured track with open-ended questions in order to define the contents to be treated without, in any way, limiting the respondents to freely communicate their opinions and experiences. Indeed, respondents were solicited to describe objectives, insights and strategies in great detail and exhaustive explanations, with specific focus depending on the subjects interviewed. This step has been implemented as a preliminary exploratory investigation with a pilot sample (see table 4.1), in order to collect reliable empirical evidences and understand key attributes and implications of the rising digital manufacturing ecosystem from the field, to be corroborated by the following phases (i.e. model refinement and quantitative phase).

Category	Firm Size	Subject interviewed	Company
1. Manufacturing Group (Automotive)	Large	Logistics Manager and responsible	Mercedes-Benz Italia
2. FabLab	/	– FabLab and Incubator managers – FabLab founder	– Bic Lazio Incubator and FabLabs – Roma Makers
3. SME (start-up)	Small	– CEO and founder – CEO and co-founder	– Eumakers – Ewe Industries
4. Manufacturing Group (Food & Beverage)	Large	Research, Development and Quality division managers	Barilla Group S.p.A.

Table 4.1. Exploratory Phase Sample

Below are summarized some results from our studies:

1. The paper sheds lights on the state of the art of Additive Manufacturing, analyzing 3D printing process phases, different techniques, industry applications, market share as well as advantages and limitations from three different viewpoints (supply side, demand side, ecological footprint). Moreover it compares this technology with mass customization and propose a matrix of 4 different scenarios related to the application of AM in the automotive industry, according to the dimensions of "technology level" and "manufacturing configuration". In particular, in a future scenario characterized by decentralized production and technological improvements in AM, the digital manufacturing of original spare parts (starting from CAD files) could be outsourced from automobile manufacturers (e.g. Mercedes-Benz) to “printer farms”, that will effectively commoditize the making of products on-demand and closer to the customers, while granting the use of original designs in exchange for payment of royalties on units sold. In addition, it was argued that in a "hybrid world" characterized by both traditional and new manufacturing processes working alongside, producers will be able to strategically decide which components should be moved to the new production processes and which ones to produce through traditional techniques (exploiting economies of scale). Thus, in order to achieve the greatest strategic advantage over competitors, companies must be able to understand what are the favorable characteristics of the different items produced to determine the right candidates for the innovative production processes.

2. Digital manufacturing labs (FabLabs), by providing the tools and computing power to make almost anything and combining entrepreneurial innovation, research and education, infuse new ideas and possibilities into global communities. These communities share projects and innovative value-added solutions, and give a boost to local entrepreneurship and job creation in a creative bottom-up collaborative approach. This concept promotes the diffusion of the digital culture through practical

training and managerial mentoring to different users/stakeholders, for the development of innovative projects.

3. Two successful Italian start-ups that developed different business models connected to the digital manufacturing ecosystem were analyzed:
    3.1. *Eumakers* is a start-up based in southern Italy (Puglia) born from the experience of its founder in the field of plastic extrusion, and in particular in the production of biodegradable and compostable bags, made of polyethylene and PLA, for separate collection. Its core business are the production and sale of PLA filaments for 3D printers, rapid prototyping online services, development of digital design and printing of original objects in 3D;
    3.2. *Ewe Industries* is a start-up founded in 2013 with headquarters in Pomezia (Rome), which deals with the design, production and sale of desktop and industrial 3D printers and extruders. The core value of the company is the attention to the recycling of raw materials and to a conscious use of them.

4. Barilla Group S.p.A. has recently developed in-house the first prototype of a 3D printer for pasta (within the "3D Pasta Printing" project – See figure 4.3).

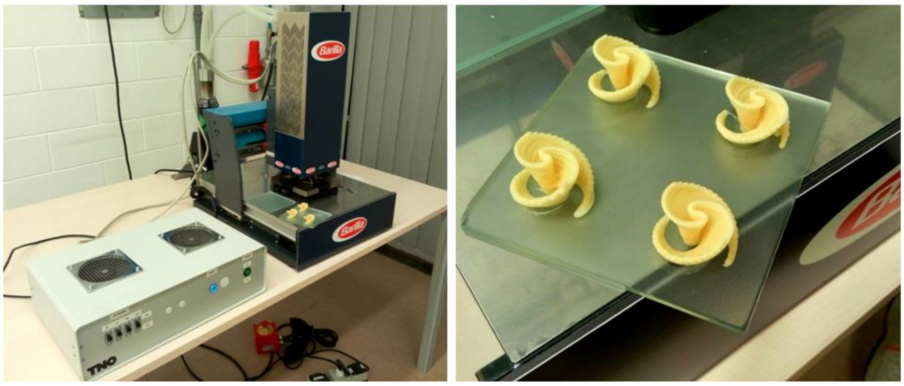


Fig. 4.3. Barilla 3D Printer (a) and 3D-Printed Pasta (b)

Potential uses of Barilla 3D Pasta Printing can be split up into the following industry levels and scenarios:

A. *Consumer produced pasta:* in this scenario Barilla would be considered the developer of the desktop 3D printer and the only supplier of the digital models for the domestic production of different types of pasta. Fabrizio Cassotta - Innovation Pasta, Ready Meals and Smart Food Manager, team leader for the 3D Pasta Printing project - highlighted that "the user interface would be as easy as possible, with plug and play cartridges and a dedicated mobile app to select the size/recipe and start the printing process". This would allow to achieve the food printing goal of producing shapes on-demand without the need for a multi-step process, enabling even less skilled users to produce any kind of fresh pasta in a short time. Furthermore it would be possible to adapt the ingredients to individual's health requirements and activity level, as well as tastes.

B. *Small scale food production:* would include mainly pasta shops, supermarkets and restaurants, both independent and directly managed by Barilla (i.e. the ones recently opened in New York). In any case, the technology and the whole service (e.g. different pasta designs, sauces, etc.) would be provided by Barilla to ensure compliance with its quality standards. Pasta can then be printed according to specific customer requirements, for the direct consumption or for purchase. "This would ensure a unique gastronomic customer experience" sustained Cassotta. Within this category is included also the idea of local *"printer farms"*, spread over the whole country and ideally comparable to FabLabs.
C. *E-commerce*: online selling of 3D printed pasta, specifically created according to the individual consumer tastes and delivered at home.
D. Concerning *Industrial scale food production,* Barilla will continue serving the mass consumer market (and the most traditional pasta formats) by using conventional manufacturing techniques, in order to avoid current technical limitations as well as to exploit economies of scale and higher efficiency in terms of production costs and times.

The evidences presented so far provide us with an initial picture on the level of awareness different sized firms have of the potential brought by the digital manufacturing ecosystem innovations as well as to identify some interesting themes and patterns to be further explored in the quantitative phase (through their inclusion in the instrument design). It resulted that, in most of the cases, firms understand the big potential of these disruptive innovations but have not yet developed capabilities and specific strategies for their application within the value chain, through the design of the most appropriate business model.

4.5 Quantitative Phase: The Use of Surveys

Due to the explanatory nature of this work as well as the positivist epistemology adopted here, a quantitative methodology has been selected to support the development of the remaining phases (Avison & Pries-Heje, 2005; Benbasat et al., 1987; Scornavacca, 2010; Straub et al., 2004; Straub, 1989). Specifically, a quantitative approach can provide statistical evidence from a large sample regarding construct validity and reliability (Avison & Pries-Heje, 2005; Babbie, 1990; Pinsonneault and Kraemer, 1993; Hair et al. 1995).
The purpose of the quantitative phase is to achieve the second and the third research objective:

- **RO2:** Explore what are the factors that drive the development of *Digital Manufacturing Capabilities*;
- **RO3:** Understand and assess the extent to which dynamic and digital manufacturing capabilities affect organizational performance.

In order to be addressed, these research objectives required a data gathering method that allowed for quantifiable descriptions of the relationships being tested.

Quantitative research methods include surveys, laboratory experiments, and numerical techniques such as mathematical modelling (Myers, 1997; Avison & Pries-Heje, 2005).

Surveys are a common data gathering method used in Social Science studies (e.g. Management, IS and Psychology fields) that are concerned with validating research models (Gefen & Straub, 2005; Venkatesh et al., 2013). Through this method it is possible to examine causal relationships between and among variables through substantial amounts of data to test the theoretical model and answer research questions (Babbie 1990; Avison & Pries-Heje, 2005). Indeed, the reduction to a parsimonious set of variables, tightly controlled through statistical analysis, provides measures and observations for testing a theory.

The survey results provide quantitative descriptions from a representative sample of a population that describe the eventual validity of hypothesized statements. These sample results can then be generalized to the entire population being studied so that inferences can be drawn about some characteristic, attitude or behaviour of this population (Creswell, 2014).

Thus an advantage of surveys is represented by the possibility to identify attributes of a large population from a smaller group of individuals (Fowler, 2009). However, there are possible issues with the use of surveys, ranging from frame bias and non-response bias to measurement problems (Pinsonneault and Kraemer 1993; Avison & Pries-Heje, 2005). These issues can be overcome by a carefully designed and methodically tested instrument, based on high quality sampling and sufficient responses (Hair, Anderson et al. 1995; Straub, Boudreau et al. 2004; Evans & Mathur, 2005; Avison & Pries-Heje, 2005), as will be described in the next chapter.

More in detail, an **online/web based survey** was developed and used to test and validate the proposed research model presented in chapter three (Gefen & Straub, 2005; Hinkin, 1998; Straub, 1989). Online surveys allow for speed and timeliness, the ability to obtain large samples, ease of data entry and analysis (Evans & Mathur, 2005).

Web-based survey involves a self-administered questionnaire delivered via web browser, in which the presence of an interviewer is not needed (Scornavacca et al., 2004). Responses are transferred electronically to a server through the Internet. Typically, respondents are provided with a survey invitation and web address via e-mail. Online surveys have numerous benefits over traditional methods (Klassen and Jacobs 2001; Scornavacca et al., 2004; Goeritz 2006). One of the main advantages is the low cost of administration, due to the "peopleless and paperless" mode of data collection (Clayton and Werking, 1988). There are, for example, no costs associated with paper, printing, envelopes, stamps, and related administrative work, or for data entry and editing. In addition, it also enables extremely large samples, which may help to reduce sampling variance (Clayton and Werking, 1988; Boyer, Olson et al. 2002; Scornavacca et al., 2004). Other benefits include the much shorter times involved in administering e-surveys, no need for data re-entry (potentially reducing mistakes due to typos and interpretation of the respondent's handwriting), and the ability to do customized e-mail follow-ups (Simsek and Veiga, 2000; Simsek and Veiga 2001; Holland, Smith et al. 2010).

On the other hand, online surveys provide some important challenges for researchers such as low response rate, non-response bias, and assuring the quality of the sampling frame (Dillman, 2000; Scornavacca et al., 2004).

In this research, the electronic medium was considered the most appropriate channel to reach a large sample (N>100) of professionals operating in the manufacturing sectors (Klassen and Jacobs, 2001; Shannon, Johnson et al. 2002; Goeritz, 2006). The speed, timeliness and ease of data entry and analysis of the online survey allowed the quantitative phase to be carried out within the project timeline. Furthermore, the benefit of having access to large data samples and complete answers through an online survey meant a higher accuracy in the generalized findings.

4.6 Data Collection and Analysis

As already mentioned in this chapter, the dataset in this research will be analyzed using the technique of Structural Equation Modeling (PLS-SEM).

Structural Equation Modeling allows the researcher to assess the overall fit of a model as well as test the structural model all together (Chin, 1998; Gefen, Straub et al. 2000). SEM evaluates an entire hypothesized multivariate model, including the hypothesized structural linkages among variables, and between each variable and its respective measures (Bagozzi and Baumgartner, 1994). It is a family of multivariate statistical techniques used to examine direct and indirect relationships between one or more independent latent variables and one or more dependent latent variables (Gefen et al. 2000).

Overall, SEM provides some advantages in comparison to path analysis and multiple regression (Bagozzi and Baumgartner, 1994; Chin, 1998; Gefen et al., 2000). SEM assesses the degree of imperfection in the measurement of underlying constructs, while regression and path analyses do not distinguish between less than perfect measurement of variables and non-random, unexplained variance (Chin, 1998). In addition, path analysis assumes that underlying constructs and the scales used to measure them are identical, whereas with SEM, the reliabilities of each of the latent variables considered in the analysis can be assessed. Furthermore, SEM allows for modeling of the unexplained variance taking into account the structural equations (Bagozzi and Baumgartner 1994). Finally, SEM offers measures of overall fit that can provide a summary evaluation of complex models (Gefen et al., 2000; Cheung and Chan 2004).

There are two main approaches within structural equation modeling: component-based (CB) approach such as Partial Least Square (PLS) and covariance based approach such as LISREL CB-SEM (Marcoulides, Chin et al. 2009; Qureshi and Compeau 2009; Wetzels, Odekerken-Schroeder et al. 2009). To understand when to use PLS-SEM versus CB-SEM, researchers must focus on the characteristics and objectives that distinguish the two methods (Hair et al., 2012).

PLS has some advantages over CB-SEM, such as allowing a smaller sample size and requiring no assumptions about the distributions of the variables (Chin, 1998; Esposito Vinzi, Chin et al., 2010). Also, PLS can be effective in situations where the theoretical underpinning of the study is at an early stage or is adapted from different settings, as in the present study (Fornell and Bookstein, 1982; Chin, 1998). In these situations where theory is less developed, researchers should consider the use of PLS-SEM particularly if the primary objective of applying structural modeling is prediction and explanation of target constructs (predictive purposes). The estimation procedure for PLS-SEM is an ordinary least squares (OLS) regression-based method rather than the maximum likelihood (ML) procedure for CB-SEM and uses available data to estimate the path relationships in the model with the objective of minimizing the residual variance (i.e. the error terms) of the endogenous constructs. In other terms, this method estimates coefficients (i.e., path model relationships) that maximize the R^2 values of the target endogenous constructs, thus minimizing the amount of unexplained variance. This feature achieves the prediction objective of PLS-SEM (Hair et al., 2014).

Therefore, PLS was considered the most appropriate method to test the research model for the following reasons. First, there is broad agreement among scholars that PLS is well suited for pilot research and theory development, which is the case in the current research study (Qureshi and Compeau 2009). Second, SEM-PLS has the potential to provide acceptable statistical power in particular for large-effect models and for non-normal data (Chin, Gopal et al. 1997). Third, PLS-SEM achieves high levels of statistical power with small sample sizes, with larger sample sizes increasing the precision (i.e., consistency) of its estimations. Greater statistical power means that PLS-SEM is more likely to render a specific relationship significant when it is in fact significant in the population, benefitting from high efficiency in parameter estimation. Forth, connected to the challenges of online surveys, PLS-SEM is highly robust as long as missing values are below a reasonable level as well as it is not affected by data inadequacies. Finally, concerning the relationships between constructs and their indicators, PLS-SEM can easily incorporate reflective and formative measurement models.

4.7 Chapter Summary

This chapter presented the research outline and discussed some important decisions concerning the methodology used to support this study. First, the selection of the research paradigm was discussed. This was followed by the presentation of the research outline and key methodological considerations such as the use of quantitative methods and online surveys. The following chapters will focus on Methodological issues regarding the instrument development as well as testing the theoretical model.

5. Chapter V: Instrument Development

5.1 Introduction

Following the clarification of the reasons behind the choice of the data gathering method (i.e. web-based survey) provided in the last chapter, the purpose of the present chapter is to explain the steps taken during the quantitative phase of this research, by particularly focusing on the development of the research instrument. To this end, the survey instrument (i.e. questionnaire) development process will be explained. Next, the survey instrument validation steps are discussed. Then, instrument design and pre-test results are explained before the instrument refinements are presented.

However, since to the best of our knowledge until now there is no validated and feasibility tested survey questionnaire available specifically designed for the assessment of antecedents and consequences of digital manufacturing capabilities, the aim of this research phase is to develop and validate a questionnaire suited to test our conceptual model.

As previously mentioned, in order to minimize measurement error, it is important to rigorously develop a reliable and valid research instrument (Churchill, 1979; Straub, 1989; Moore and Benbasat, 1991; Hinkin, 1998).

In accordance with Gefen, Straub et al. (2000), the fundamental evaluation criteria for instrument development are **content validity**, **construct validity**, and **reliability**.

Content validity is a qualitative evaluation of the extent to which the measures of a construct actually capture its real nature. Usually, It is established through a pre-test used to eliminate measurement error caused by poorly worded or ambiguous questions or instructions, ensuring that all questions are appropriate and understood (Gefen, Straub et al., 2000).

Construct validity assesses whether the measures chosen are true measures of the constructs describing the phenomenon or if they are simply artefacts of the methodology per se (Cronbach 1971; Gefen, Straub et al. 2000). If constructs are valid, one can expect quite high correlations between measures of the same construct using different measurement items, and low correlations between measures of constructs that are expected to differ (Campbell and Fiske, 1959; Hair, Anderson et al., 1995). In other words, If an item is consistently placed within a particular category, it is considered to demonstrate convergent validity with the related construct, and discriminant validity with the others (Moore & Benbasat, 1991).

Reliability indicates the extent to which measurements are repeatable (Straub 1989; Straub et al. 2004). The reliability of a multi-item measure can be estimated by Cronbach's alpha (α) and Composite Reliability (CR) (Cronbach, 1971; Fornell and Bookstein, 1982; Field, 2009).

A dynamic web-based questionnaire for investigating the constructs of the research model and testing the hypotheses developed in Chapter 3 was designed, then systematically validated by experts and academics through a face validation for content relevance and simplicity. This phase was iteratively followed by revisions and finally the instrument/web-based survey was pre-tested for its feasibility. Figure 5.1 illustrates the steps followed for the instrument development.

The validation process substantially improved the relevance and the simplicity of the questionnaire and the pre-test confirmed the feasibility (de Alwis et al., 2016).

Instrument Design

- Specify Construct Domain
- Sample Item Generation
- Expert Review
- Survey Design
- Survey Pre-test
- Instrument Refinement

Figure 5.1. Instrument Design Process

The first step in the instrument development process usually consists of specifying the domain of the constructs which form the research model, where the researcher clarifies their definition, indicating what is included and what is excluded in that given domain (Churchill, 1979; Moore and Benbasat, 1991; Hinkin, 1998; Scornavacca, 2010). This stage has been already discussed in the development of the research model in Chapter 3. The remaining stages represented in figure 5.1 will be described in the subsequent sections.

5.2 Generation and validation of Items

The next step was to generate items to represent the research constructs within that domain (MacKenzie et al., 2011).

According to Moore and Benbasat's (1991) work, this research used the following guidelines for developing or adapting items that reflected the research model:

1) examine literature;

2) purify/create new items where necessary;

3) develop scales for items.

Thus, the initial questionnaire was developed based on a literature review and adjusted to fit the content domain. Literature related to the research topic was examined to seek items from existing, already validated scales, that reflected the research model (de Alwis et al., 2016; Hinkin, 1998; Mitra et al., 2011; Moore & Benbasat, 1991; Pinsonneault & Kraemer, 1993). Potential items were reviewed with careful consideration. It was ensured that the items aligned well with the research constructs in the research model. For instance, the dimension of Digital Mindset (DM) was derived and rephrased from the scale of Multimedia Mindset retrieved from the study of Karimi & Walter (2015).

As a result of the analysis of literature, the items were derived from disciplines including Strategic Management, Organisational Studies, IS and Psychology. To begin with items retrieved from the literature is considered an efficient step in item development, since it allows the researcher to work with pre-tested items, saving time and providing reliable items (Boudreau, Gefen & Straub, 2001).

As a second step, items were purified to suit the context of the study. Consecutively, some items were re-worded when necessary. Completely new items were also added to constructs that were not covered by the academic literature reviewed, especially for DMC (Moore & Benbasat, 1991). These new items were added to ensure that the constructs were fully reflected by the questionnaire. Contrariwise, items that were out of the domain or scope of the research were not taken into account. The development of some of these new items was also inspired by assessing specific industry reports and practitioners' articles focused on the topic of digital transformation, in addition to academic literature.

Some criteria were taken into account to assess or generate the items in this research. According to past research, indeed, items should be as short as possible and the language used should be familiar to target respondents (Hinkin, 1998; Moore and Benbasat, 1991). Additionally, to avoid confusion, researchers should not use double-barrelled items that seek more than one issue nor ambiguous and redundant items. Furthermore, in some cases reverse-coded items can be used to reduce bias; however, they need to be clear and not add confusion (Dillman et al., 2008; Price & Mueller, 1986).

Even if it is commonly suggested that keeping an instrument short is an effective way of minimizing participants' boredom and fatigue - which can help avoid a low response rate - it is also crucial that each construct is adequately sampled (Chin, Gopal et al. 1997; Churchill, 1979; Straub, Boudreau et al. 2004). Therefore, every construct of the instrument was measured by a number of items between four and twelve.

Third step, scales were developed for each dimension in the survey instrument (Moore & Benbasat, 1991). Likert-type scales are the most frequently used in survey instruments and ensure reliability and validity of measurements (Hinkin, 1998; Edwards & Smith, 2016). Particularly, 5-point Likert scales and specific labeling of points were adopted to indicate the degree of **agreement** (ranging from “strongly disagree” to “strongly agree”), **frequency** (ranging from “never” to “always”), **likelihood** (ranging from “not considering at all” to “currently using”), and **relevance** (ranging from “very low” to “very high”).

Although Renis Likert, who first introduced the Likert scale in 1932, advocated the use of the 5-point scale, other researchers have argued for more points to increase the reliability and validity of the scale. Weijters, Cabooter, and Schillewaert (2010) found that more options (e.g. 7-point scales) decreased the occurrence of extreme response styles, and Lozano, Garcia-Cueto, & Muniz (2008) noted that reliability increases when there are more points (Edwards & Smith, 2016). On the other hand, fewer categories in a scale can help in reducing the cognitive load for the participant that is involved in providing a response. According to Dillman et al. (2008), a scale needs to be long enough to represent the entire continuum of possible answers but without so many options that may burden the respondents, or that the difference between any two categories becomes so small that it is meaningless. Feedbacks from our survey pre-test largely supported the choice of a 5-point Likert scale.

5.3 Validity Assessment: Expert Panel Review

Several rounds of expert review and proof reading occurred to ensure the items clearly reflected the respective construct definitions. Indeed the questionnaire was developed in English, reviewed and then translated into Italian, in order to reach a wider sample of respondents. The translated version was proofread by an expert translator and followed the same pre-test process of the English version.

According to Straub (1989), it is important to conduct several rounds of instrument pretesting with different groups of expert judges or panels in order to establish content validity.

Throughout the process of the initial items development, several draft versions of the items were formally reviewed by senior Management and IS scholars. This process achieved content validity to ensure the items representing the constructs being measured as well as assisting in item reliability (Boudreau & Straub, 2001; Straub et al., 2004). It was also critical to maximise comprehension and avoid measurement error of items (Dillman et al., 2008).

The validation process was performed through consecutive assessment stages. In each stage, experts assessed the questions individually and as a questionnaire tool, with respect to their content relevance and simplicity. The questionnaire assessment document was emailed to the experts in MS Word format to enable track changes and comments, or presented through face-to-face meetings with each expert. The questionnaire document incorporated a clear and comprehensive introduction to its topics and purposes, all items and response options, construct definition, and specific instructions for its completion. Experts were requested to analyse the material and provide feedback on the following areas:

- Were the scales consistent with the domain under investigation and the construct measured?
- Was the content clear?
- Did the proposed grouping of the items seem logical?
- Did the instrument measure the right content?

At the end of each stage, the questionnaire was revised with the supervision of a senior academic, according to the experts' comments and annotations (Grant & Davis, 1997; Polit & Beck, 2006). The initial pool of generated items were rephrased whenever they confused the judges of the respondents, or deleted whenever ambiguous, overlapped with other items, or whether they seemed to capture a meaning/content different from the one they were selected for. In addition, especially concerning the construct of DMC, some experts suggested to merge some items together. For instance the categories of product design and development, which at the beginning were separate items (see Dig_Inn_D&D).

The **academic panel** members were selected based on their individual expertise in questionnaire design and survey deployment or in the specific domain of the constructs. They work in Italian and American Universities. The expert panel was composed of the members indicated in the following table:

Expert	Role	Gender	Domain
1.	Associate Professor	Female	Business Management/Marketing
2.	Associate Professor	Female	Management
3.	Associate Professor	Female	Strategic Management
4.	Associate Professor	Male	Management Information Systems
5.	Assistant Professor	Male	International Business and Strategy
6.	Full Professor	Male	Business Management/Marketing
7.	Associate Professor	Male	Management Information Systems
8.	Associate Professor	Male	Innovation/Quality Management
9.	Associate Professor	Male	Financial Management
10.	Associate Professor	Male	Psychometrics

Table 5.1. Academic Experts Panel

After this phase, some scales present in the initial pool of items such as *Relative Advantage* (retrieved from Moore and Benbasat, 1991; Venkatesh et al., 2012) and *Adoption Category* (retrieved from Yi et al., 2006, as adopted in Schniederjans, 2017) were completely excluded since they were not relevant to the domain of the constructs to be measured and neither fully consistent with the purpose of the paper. Furthermore, the *Use of Technological Innovations* scale, instead, was moved from the questionnaire section measuring the construct of Digital Manufacturing Capabilities (DMC), to the final part as a control variable (see section 5.5.4). Finally, an item was added to the scale measuring Autonomous Innovation Teams (AIT).

The **professional panel** included senior managers from manufacturing companies and business consultants (operating both in Italy and abroad), who were asked to review preliminary as well as subsequent versions of the questionnaire to be used in the survey study while providing feedbacks on the clarity of items as well as difficulties in responding to them. In particular, managers often highlighted the following actions:

- Simplify the questionnaire by eliminating questions which may be redundant
- Keep terminology consistent (e.g. Firm vs. Organization/Company)
- Keep all questions grammatically consistent in present tense
- Avoid acronyms (e.g. IoT described as Internet of Things).

Even in this case, as a result of this process, several questionnaire items were reworded, merged or eliminated (Oliver Schilke, 2014). In particular, the sub-dimension of Autonomous Growth Group (AGG) was renamed as Autonomous Innovation Teams (AIT) to better reflect the nature of the concept investigated. In addition, the scales of Digital Innovations for Product Design and Development (i.e. Dig_Inn_D&D) and Digital Innovations for Manufacturing (i.e. Dig_Inn_Man) were significantly improved concerning their technical contents.
The professional experts panel was composed of the members indicated in the following table:

Expert	Gender	Role in the Organization / Expertise
1.	Male	Vice President, Business Process Management
2.	Male	Plant Manager
3.	Male	Director, IS Services Management
4.	Male	Vice President, IS Demand Management
5.	Male	Director, IS Enterprise Architecture
6.	Male	Senior Manager, Enterprise Process Management
7.	Male	Head of Procurement Components & Services
8.	Female	Product Marketing Manager
9.	Male	Business Consultant, Business Networks
10.	Male	Supply Chain Management Consultant, International Contracts

Table 5.2. Professional Experts Panel

Taken as a whole, the expert panel was a valuable step in the development of the questionnaire. The rich and insightful ideas provided by the panel allowed the researcher to further improve the content validity of the constructs and to fine-tune several items.

5.4 Survey Design and Pre-test

As discussed in the previous chapter, the data collection process in this study was carried out using a web-based survey. Thus, once the scales were finalized, the next stage of the instrument design concerned the development of the online questionnaire (Scornavacca, 2010; Simsek and Veiga, 2001). An important goal in survey design is to make it in such a way as to reduce non-response rate as much as possible (Hair, Anderson et al. 1995; Dillman 2000; Scornavacca et al., 2004). In order to increase participation in the online questionnaire, the survey response process was streamlined by paying meticulous attention to its layout, flow and wording (Evans and Mathur, 2005; Holland et al. 2010). The layout of the survey items was simply formatted (following experts' suggestions) to avoid any clutter (Simsek & Veiga, 2000). The answer boxes used were simple; complex graphic or interactive functions were not included to avoid any possible source of confusion. In addition, the order of survey items and sections was the most logical as possible.

The online survey questionnaire was structured as follows:

Sections	**Content**
A. Pre-Survey	– Consent – Survey Introduction and researcher contact
B. Survey Questionnaire	Part 1 - Questions Related to High Order Dynamic Capabilities Construct
	Part 2 – Questions Related to DMC Construct
	Part 3 – Questions Related to Performance Construct
	Part 4 – Demographics and Control Variables
C. Post Survey	– Thank you note

Table 5.3. Structure of the Online Survey

For the next step of this research, the survey instrument was uploaded to the online software provider. Firstly, it was uploaded to the Google Forms[2] platform, and then using SurveyMonkey[3] software for the definitive version. This second choice was driven by the availability of a more complete kit of tools and export/analysis options on SurveyMonkey platform, as decided after a brief pre-test with three participants.

In the introduction of the survey (i.e. Pre-Survey section), information regarding some key definitions of the research settings, the goal and focus of the research, participation criteria, confidentiality, anonymity, management of collected data and voluntariness was highlighted. Also, information regarding incentives was emphasized by offering respondents a summary of the completed study and the possibility to directly contact the researcher for further information or for receiving insights on the final results (Göritz, 2006; Simsek & Veiga, 2000). A consent question then followed this. The Survey introduction page is showed in

[2] https://www.google.com/forms/
[3] https://it.surveymonkey.com/

the figure below (see figure 5.2). Particularly, the introduction to the survey questionnaire was designed to clarify key terms such as “Digital Transformation” and “Smart Manufacturing”, and to emphasize the exact focus of the research.

Digital Manufacturing: How Digital Transformation is Reshaping the Manufacturing Sector

Digital technologies, adopted by a large number of manufacturers around the world, are rapidly transforming the industrial sector as well as every aspect of everyday life.

The phenomenon of Digital transformation of manufacturing sector (also known as "Industry 4.0" or "Smart Manufacturing") is finding a growing interest at both practitioner and academic levels, but it is still in its infancy and needs deeper investigation.

The goal of this survey is to understand the degree of implementation of digital technologies and skills within manufacturing companies, by analyzing the factors influencing their use and their impact on business performance.

This information will be crucial to identify what are the capabilities that companies need to develop in order to successfully implement the digital transformation and address the dynamic environmental change.

This survey is anonymous. Collected data will be held in strict confidentiality and used only for the purposes of this research. The results will be reported in aggregate form only, without any identifiable personal information.

The Head of the **Management Department** at **Sapienza University of Rome** has approved this research project.

Your participation is voluntary, and you are implying consent to participate by completing and submitting this online survey. It should take you about 15 minutes to complete it.

The aggregate data will be stored in a password-protected file.

If you would like to receive a summary of the results or if you have any questions about it, please contact Marco Savastano at the following email address: **marco.savastano@uniroma1.it**

Thank you for your cooperation. Your contribution will allow the advancement of research on this topic.

Fig. 5.2. Capture of the Pre-Survey Section

Once the survey system was up and working, a pre-test was conducted. Pre-tests are conducted with the purpose to assess that the mechanics of compiling the questionnaire are adequate (Moore and Benbasat, 1991; Hinkin, 1998; Field, 2009). A sample of 6 participants was asked to test the online questionnaire. The survey was tested on mobile and online platforms to ensure the survey functioned appropriately. This included testing the survey on multiple mobile operating systems such as Android, iOS and Microsoft. Different browsers (e.g. Internet Explorer, Firefox, Google Chrome, Safari) were used during the test. In addition, a test of the data collection and conversion process (to Excel and SPSS software) was carried out. Participants were asked to complete the questionnaire and then comment on matters such as clarity, length, wording, flow, and timing (Babbie, 1990; Simsek and Veiga, 2001).

The pre-test sample is represented in the following table:

Expert	**Domain of expertise**	**Profession**
1	Digital Media Management	Digital Media Specialist
2	Corporate Governance	Internal Auditor
3	IT and Finance	Functional Analyst
4	Psychology	Full Professor
5	Supply Chain Management	Chemical Engineer
6	Computer Science, AI	Ph.D. Candidate

Table 5.4. Survey Pre-test Panel

On average, each participant took between 15 and 20 minutes to complete the survey. After completing the survey, participants were asked to report on content clarity as well as any issues they may have encountered with the system when answering the questionnaire. Their feedback provided important suggestions on how to improve the wording of the instructions as well as the sequence in which some questions were presented. These suggestions were taken into consideration and several small changes were made to the questionnaire. No major issues were reported in relation to the construct items.

For instance, based on their feedback a few spelling errors were corrected and few questions were rephrased. In Part 3 the Likert scale measuring the *Perceived Innovation Performance* dimension (Perc_Inn_Perf) was modified to reflect more clearly the actual perceptions of the participants. Concerning firm's perceived financial and market performance, initially included in a single dimension, they were separated into two dimensions to provide participants with greater clarity: Perceived Financial Performance (Perc_Fin_Perf) and Perceived Market Performance (Perc_Mkt_Perf). In addition, especially in Part 4, the option "other" was added to some demographic questions (e.g. concerning the industry). Moreover, some issues related to the layout of these questions were raised and consequently revised.

Overall, running the survey pre-test using a sample of six professionals from different backgrounds was extremely beneficial for improving content validity, fine-tuning the questionnaire layout as well as testing the usability and reliability of the online instrument (Hinkin, 1998; Scornavacca et al. 2004). Based on the feedback received, even some spelling errors were corrected in order to improve the questionnaire's flow. The finalized questionnaire used in this study is available online at the following link: *https://it.surveymonkey.com/r/W5ML8GB*

The following subsections describe in detail the definitive items for each specific construct, as refined during the previously described phases.

5.5 Final Instrument

As a consequence of the development and refinement process described so far, the final survey instrument consisted of 85 items. In the following sections these measurement items will be presented in details along with their dimensions and construct definition (see Tables below).

5.5.1 High-Order Dynamic Capabilities

As already discussed in Chapter 3, in this study the construct of **High-Order Dynamic Capabilities (HODC)** is defined as the *capacity of a firm to systematically change its specific resource base in terms of resources-processes-values (RPV) to improve its competitive position in a fast changing economic context.*

Thus, the construct of High-Order Dynamic Capabilities is measured by assessing the strengths and weaknesses of a manufacturing company's RPV for effectively managing innovation projects and responding to digital disruption.

According to the RPV theoretical framework, in the present study the following dimensions represent different facets of High-Order Dynamic Capabilities:

- **Resources**: assess the extent to which a manufacturing company has dedicated financial resources (DFR), dedicated human resources (DHR), and top management support (TMS) for fostering digital transformation. These assets are intangible in nature and need to be built and cultivated over time (Barney, 1991; Christensen & Raynor, 2003).

  Resources are measured by three reflective factors: DFR, DHR, and SMS.
  DFR assesses the extent to which a manufacturing company dedicates adequate financial resources to responding to digital disruption and facilitating new growth.
  DHR measures the extent to which a manufacturing company dedicates sufficient human resources with specific skills to address its digital strategy.
  TMS assesses the extent to which senior managers of manufacturing companies support innovative project teams to improve new ideas, developing and communicating a vision and providing resources to support initiatives.

- **Processes:** assess the extent to which organizations create value by transforming inputs of resources—people, equipment, technology, product designs, brands, information, energy, and cash—into products and services of greater worth, through the interaction, coordination, communication, and decision-making activities. They are the fundamental pillars of organizational capability and competitive advantage (Kohli & Melville, 2009; Ray et al., 2004).

  More in detail, they assess the extent to which a manufacturing company has established processes for staged allocation of resources (SAR) for developing digital innovation projects, and autonomous innovation teams (AIT).

  Processes are measured by two reflective factors: SAR and AIT.

  SAR assesses the extent to which a manufacturing company takes a trial-and-error approach to digital innovation projects.

  AIT measures the extent of the growth group's ability to be self-directed and the extent of its authority to make decisions in developing digital innovation projects.

- **Values:** values of an organization are the criteria by which firms make decisions about priorities, at every level. They are the primary building-blocks for culture, which is the pattern of shared values, norms and practices that distinguishes one organization from another.

  Values assess the extent to which a manufacturing company establishes an innovative culture (IC), a common language (CL) and a digital mindset (DM) necessary for creating an innovation-supportive culture.

  Values are measured by three reflective factors: IC, CL, and DM.

  IC measures the extent to which a manufacturing company encourages experimentation and rewards innovative behavior.

  CL assesses whether (1) various stakeholders in a manufacturing company understand and have a shared perspective on the key innovation principles, (2) they see their roles in it, and (3) the core concepts reflecting the key innovation principles are built into company documents and stakeholders share the same principles.

  DM measures the extent to which a manufacturing company incorporates digital innovation into its culture.

The following tables will show the items that measure the construct of High Order Dynamic Capabilities, through the different dimensions outlined.

For the first construct – Higher Order Dynamic Capabilities - items were outlined to produce a statement to which the respondent was asked to indicate a degree of agreement in a five-point Likert scale ranging from "strongly disagree" to "strongly agree" (Field, 2009; Hair et al., 1995; Hinkin, 1998).

HIGH-ORDER DYNAMIC CAPABILITIES (HODC)			
	RESOURCES		
Dedicated Financial Resources (DFR1-DFR7)			
Code	**Item**	**Action**	**Source**
DFR1:	My organization allocates adequate funds for the research and development of innovative digital technologies (ICT) to support business process	Derived	Karimi & Walter, 2015 *α = 0.80*
DFR2:	My organization allocates adequate funds for the adoption of innovative digital technologies (ICT) to support business process	Derived	
DFR3:	My organization allocates adequate funds for continuous training of employees for the use of innovative digital technologies (ICT)	New Item	
DFR4:	My organization consistently devotes funds to new growth through innovative digital technologies (ICT)	Adapted	
DFR5:	My organization constantly increases funds dedicated to digital innovation projects	New Item	
DFR6:	In my organization there is adequate committed funding for the development of innovative/smart products	New Item	
DFR7:	In my organization there is adequate committed funding for the production of innovative/smart products	New Item	
Dedicated Human Resources (DHR1-DFR5)			
DHR1:	My organization dedicates sufficient human resources to the development of innovative digital technologies (ICT)	Adapted	Karimi & Walter, 2015 *α = 0.75*
DHR2:	My organization dedicates sufficient human resources to the use of innovative digital technologies (ICT)	Derived	
DHR3:	Our staff have the skills needed to develop innovative digital technologies	Adapted, re-worded	
DHR4:	Our staff have the skills needed to use innovative digital technologies	Adapted, re-worded	
DHR5:	Our key people have the skill set to support the company's digital strategy	Derived	
Top Management Support (TMS1- TMS5)			
TMS1:	Top management gives priority and visibility to digital innovation projects	Adapted, re-worded	(Karimi & Walter, 2015; Karimi et al., 2007) *α = 0.91*
TMS2:	Top management actively supports digital innovation projects	New item	
TMS3:	Top management shows great interest and enthusiasm throughout digital innovation projects	Adapted, re-worded	
TMS4:	Top management invests a large percentage of its time on the company's digital innovation projects	Adapted, re-worded	
TMS5:	The overall level of top management commitment to the company's digital innovation projects is quite high.	Adapted, re-worded	

PROCESSES			
Autonomous Innovation Teams (AIT1-AIT4)			
AIT1:	Our innovation teams have substantial discretion over which digital innovation projects to pursue.	Adapted, re-worded	(Karimi & Walter, 2015; Walter & Lopez, 2008) *α = 0.94*
AIT2:	Our innovation teams have control over resources necessary for developing digital innovation projects.	Adapted, re-worded	
AIT3:	Our innovation teams have control over development processes of digital innovation projects.	Adapted, re-worded	
AIT4:	Our innovation teams have a high degree of autonomy in their decision-making process.	New Item	
Staged Allocation of Resources (SAR1 - SAR4)			
SAR1:	When we develop digital innovation projects, we expect and allow for revisions and course corrections based on what we learn as we go	Adapted, re-worded	(Karimi & Walter, 2015) *α = 0.78*
SAR2:	When we develop digital innovation projects, we keep investment small so we can afford to invest in second and third iterations.	Adapted, re-worded	
SAR3:	When we develop digital innovation projects, we use small investments to assess feasibility of these projects.	Adapted, re-worded	
SAR4:	When we develop digital innovation projects, we encourage intelligent risk-taking	Adapted, re-worded	
VALUES			
Innovative Culture (IC1 - IC4)			
IC1	Our culture encourages people to look beyond the boundaries of our current business practices and our conventional business model.	Adapted, re-worded	(Karimi & Walter, 2015) *α =0.82*
IC2	We accept and implement ideas that were "not invented here"	Adapted, re-worded	
IC3	Our culture encourages the development of new, innovative processes	New Item	
IC4	Our culture encourages the development of new, innovative products	Unchanged	
Common Language (CL1 - CL5)			
CL1	Core concepts reflecting our key innovation principles are built into company documents.	Adapted, re-worded	(Karimi & Walter, 2015) *α =0.88*
CL2	Our employees are trained in our key innovation principles	Unchanged	
CL3	Everyone in our organization understands our plan for change and sees his/her role in it	Unchanged	
CL4	There is a shared perspective on key innovation principles - from front line to senior leadership	Unchanged	
CL5	Investors and stakeholders understand and share our perspective on key innovation principles	Adapted, re-worded	
Digital Mindset (DM1 - DM8)			

DM1	We see ourselves as digital innovators	New Item	
DM2	Our organization's vision embraces digital innovation	New Item	Inspired by "compatibility" construct's measures from: (Olson & Boyer, 2003 as reported in Schniederjans, 2017) *α =0.990*
DM3	We see our role as leveraging innovative digital technologies to improve our products and services	Derived	(Karimi & Walter, 2015) *α =0.87*
DM4	We see our role as leveraging from innovative digital technologies to improve our business process	New Item	
DM5	We see digital strategy as an overall strategy of our organization	New Item	Inspired by "compatibility" construct's measures from: (Olson & Boyer, 2003 as reported in Schniederjans, 2017) *α =0.990*
DM6	We see ourselves as a digitally enabled manufacturing company	New Item	
DM7	We use digital innovation to meet market needs	New Item	
DM8	We view our organization as a cyber-physical system	New Item	

Table 5.5. HODC Scales

5.5.2 Digital Manufacturing Capabilities (DMC)

As already discussed in Chapter 3, in this study a new construct was developed to assess a firm's dynamic capabilities connected to the digital transformation of manufacturing. Particularly, the construct of **Digital Manufacturing Capabilities** has been defined as *the extent to which manufacturers use digital disruptive technological innovation to reconfigure their distinctive operational capabilities and resources (i.e. enhancing the design/development, manufacturing and features of their products), in order to meet the competitive needs of the firm.*

Therefore, in the present work the construct of Digital Manufacturing Capabilities (DMC) assess the degree to which a manufacturing company implements digital disruptive innovations to:

(1) Support product design & development

(2) Improve manufacturing process, and

(3) Enhances products' features.

DMC is measured as a reflective construct with three factors: *Digital Innovations for product design and development* (Dig_Inn_D&D), *Digital Innovations for manufacturing* (Dig_Inn_Man), and *Digital Innovations for Products' features* (Dig_Inn_Prod).

Items measuring the DMC construct were outlined to produce a statement to which the respondents were asked to indicate the frequency on a five-point Likert scale ranging from the following anchors: from (1) “never” to (5) “always”.

DIGITAL MANUFACTURING CAPABILITIES (DMC)			
Digital Innovations for Product Design and Development (Dig_Inn_D&D1 - Dig_Inn_D&D6)			
Code	**Item**	**Action**	**Source**
Dig_Inn_D&D1	My organization uses digital technologies such as Additive Manufacturing tools (e.g. Rapid Prototyping, 3D Printing, etc.) to support product design and development	New Item	**Inspired by the studies of:** Sabramani (2004); Venkatesh et al. (2012) as reported in Schniederjans (2017) *α =0.990* Tag Innovation School, (2017) Accenture Strategy (2017)
Dig_Inn_D&D2	My organization uses digital technologies such as Simulation tools (e.g. virtual machines, etc.) to support product design and development	New Item	
Dig_Inn_D&D3	My organization uses computer-aided technologies (e.g. CAD, CAE, etc.) to support product design and development	New Item	
Dig_Inn_D&D4	My organization uses digital technologies such as big data analytics to support product design and development	New Item	
Dig_Inn_D&D5	My organization uses digital technologies such as cloud computing platforms to support product design and development	New Item	
Dig_Inn_D&D6	My organization uses collaborative technologies (e.g. discussion forums, audio and video conferencing, enterprise knowledge portals, business directories) to support product design and development	New Item	
Digital Innovations for Manufacturing (Dig_Inn_Man1 - Dig_Inn_Man10)			
Dig_Inn_Man1	My organization uses digital technologies such as Additive Manufacturing tools (e.g. 3D Printing, etc.) to improve manufacturing processes	New Item	**Inspired by the following studies:** Sabramani (2004); Venkatesh et al. (2012) as reported in Schniederjans (2017) *α =0.990*
Dig_Inn_Man2	My organization uses digital technologies such as computer-aided technologies (e.g. CAM, etc.) to improve manufacturing processes	New Item	
Dig_Inn_Man3	My organization uses digital technologies such as Big Data Analytics to improve manufacturing processes	New Item	
Dig_Inn_Man4	My organization uses digital technologies such as cloud computing platforms to improve manufacturing processes	New Item	
Dig_Inn_Man5	My organization uses digital technologies such as Data processing systems (e.g. ERP, MES, PLM, etc.) to improve manufacturing processes	New Item	
Dig_Inn_Man6	My organization uses digital technologies such as advanced robotics and automation systems (i.e. autonomous and/or collaborative robots, advanced manufacturing systems, cyber-physical systems, etc.) to improve manufacturing processes	New Item	
Dig_Inn_Man7	My organization uses digital technologies such as	New Item	

	Augmented Reality tools(e.g. smart glasses, etc.) to provide workers with real time information and improve manufacturing processes		Tag Innovation School, (2017) Accenture Strategy (2017)
Dig_Inn_Man8	My organization uses digital technologies such as Simulation tools (e.g. virtual machines, etc.) to improve manufacturing processes	New Item	
Dig_Inn_Man9	My organization uses digital technologies such as Mobile devices (e.g. smartphones, tablets, wearables, etc.) to improve manufacturing processes	New Item	
Dig_Inn_Man10	My organization uses collaborative technologies (e.g. discussion forums, audio and video conferencing, enterprise knowledge portals, business directories, etc.) to improve manufacturing processes	New Item	
Digital Innovations for Products' Features (Dig_Inn_Prod1- Dig_Inn_Prod6)			
Dig_Inn_Prod1	We embed digital technologies such as Internet of Things (e.g. smart sensors, cameras, QR/RFID tags, antennas, microprocessors etc.) into our products for enhancing their features	New Item	**Inspired by the following studies:** (Porter & Heppelmann, 2014, 2015)
Dig_Inn_Prod2	We embed digital technologies such as IoT (e.g. smart sensors, cameras, QR/RFID tags, antennas, microprocessors, etc.) into our products to receive data for monitoring their use and performance	New Item	
Dig_Inn_Prod3	My organization designs and develops digitally enabled smart products	New Item	
Dig_Inn_Prod4	My organization produces digitally enabled smart products	New Item	
Dig_Inn_Prod5	We embed software into our products in order to keep them updated over time	New Item	
Dig_Inn_Prod6	We have developed digital platforms (e.g. websites, cloud platforms, etc.) to support/enhance product use	New Item	

Table 5.6. DMC Scales

5.5.3 Performance

As extensively discussed in Chapter 3, the dependant variable of the present research model is Firm Performance. In this study, the construct of performance will be understood as the *internal (performance gains overtime) and external (competitive advantage measured at industry level) outcome a firm can obtain by dynamically responding to the contextual change (in the manufacturing sector) through the development of new capabilities and resources, based on managers' evaluations*.

Performance assesses the degree to which a manufacturer's Perceived Innovation Performance (Perc_Inn_Perf), Perceived Financial Performance (Perc_Inn_Perf) and Perceived Market Performance (Perc_Mkt_Perf) increased by developing and using new specific digital capabilities and assets.

Performance is measured as a reflective construct with three factors: Perc_Inn_Perf, Perc_Fin_ Perf and Perc_Mkt_ Perf.

Scales measuring the Performance construct were outlined to indicate the degree of *relevance* (ranging from (1) “very low” to (5) “very high”) concerning the Perc_Inn_Perf, and of *agreement* (ranging from (1) strongly disagree to (5) strongly agree) for Perc_Fin_ Perf and Perc_Mkt_ Perf.

PERFORMANCE

Perceived Innovation Performance (Perc_Inn_Perf1 - Perc_Inn_Perf12)

Code	Item	Action	Source
Perc_Inn_Perf1	To my knowledge the digital innovation efforts my organization provided in the last 3 years has led to increasing the sales	New Item	**Inspired by the following studies:** Moore & Benbasat, (1991) *α =0.969* Venkatesh et al., (2012) *α =0.996* Carmeli et al., (2007) *α =0.74* Laaksonen & Peltoniemi, (2016) Militaru et al., (2017) Delaney & Huselid, (1996) *α =0.85* *α =0.86*
Perc_Inn_Perf2	To my knowledge the digital innovation efforts my organization provided in the last 3 years leaded to raising the market share	New Item	
Perc_Inn_Perf3	To my knowledge the digital innovation efforts my organization provided in the last 3 years leaded to raising its profitability	New Item	
Perc_Inn_Perf4	To my knowledge the digital innovation efforts my organization provided in the last 3 years leaded to raising its productivity	New Item	
Perc_Inn_Perf5	To my knowledge the digital innovation efforts my organization provided in the last 3 years leaded to raising its flexibility	New Item	
Perc_Inn_Perf6	To my knowledge the digital innovation efforts my organization provided in the last 3 years leaded to reducing our organization's cost structure	New Item	
Perc_Inn_Perf7	To my knowledge the digital innovation efforts my organization provided in the last 3 years leaded to reducing our time to market	New Item	
Perc_Inn_Perf8	To my knowledge the digital innovation efforts my organization provided in the last 3 years leaded to enhance our employees efficiency and efficacy on the job	New Item	
Perc_Inn_Perf9	To my knowledge the digital innovation efforts my organization provided in the last 3 years leaded to developing of innovative products	New Item	
Perc_Inn_Perf10	To my knowledge the digital innovation efforts my organization provided in the last 3 years leaded to raising products’ quality	New Item	
Perc_Inn_Perf11	To my knowledge the digital innovation efforts my organization provided in the last 3 years leaded to increasing customer satisfaction	New Item	
Perc_Inn_Perf12	To my knowledge the digital innovation efforts my organization provided in the last 3 years leaded to increasing customer willingness to pay a premium price (WTP)	New Item	

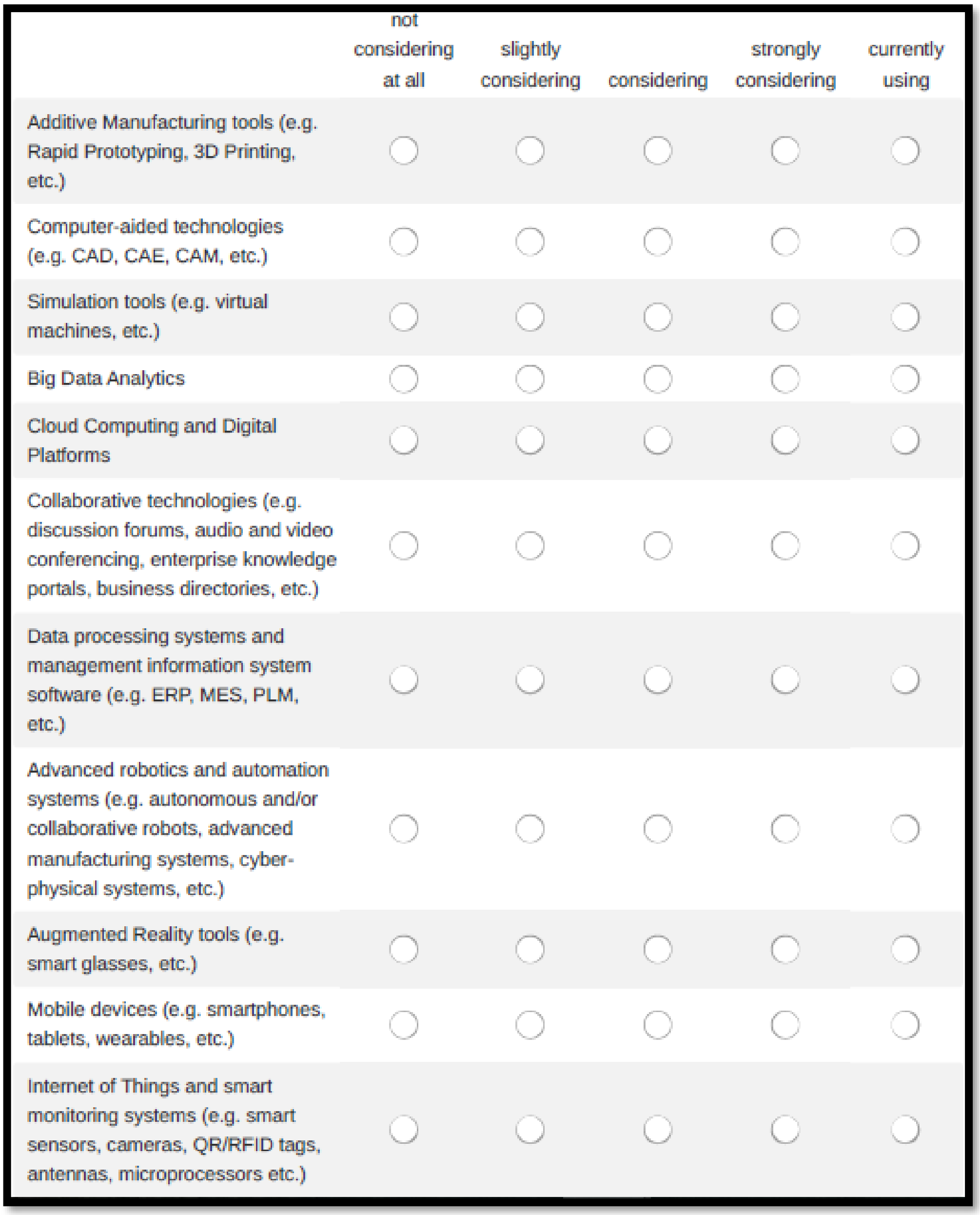
Perceived Financial Performance (Perc_Fin_Perf1 - Perc_Fin_Perf6)			
Perc_Fin_Perf 1	Our EBIT (Earnings Before Interest and Taxes) is continuously above industry average	Unchanged	Schilke, (2014) α =0.93 Griffin & Mahon, (1997) (Source For Variables Used to Measure Financial Performance)
Perc_Fin_Perf 2	Our EBITDA (Earnings Before Interest, Taxes, Depreciation and Amortization) is continuously above industry average	Derived	
Perc_Fin_Perf 3	Our ROI (Return on Investment) is continuously above industry average	Unchanged	
Perc_Fin_Perf 4	Our ROS (Return on Sales) is continuously above industry average	Unchanged	
Perc_Fin_Perf 5	Our net income (earnings) is continuously above industry average	Derived	
Perc_Fin_Perf 6	Our sales are continuously above industry average	Derived	
Perceived Market Performance (Perc_Mkt_Perf1- Perc_Mkt_Perf3):			
Perc_Mkt_Perf 1	We continuously gain strategic advantages over our competitors	Adapted, re-worded	Schilke (2014) α =0.73
Perc_Mkt_Perf 2	We have a large market share	Unchanged	
Perc_Mkt_Perf 3	Overall, we are more successful than our major competitors	Unchanged	

Table 5.7. Performance Scales

5.5.4 Control Variables and Demographics

As anticipated at the beginning of this chapter, the last part of the questionnaire (Part 4) includes multiple choice, closed-ended question type, allowing respondents to select one or multiple answers from a defined list of choices. These questions concern data relating to participants' demographics (e.g. gender, age, years of experience in the same organization, respondent's position and role in the organization) and firm's characteristics (e.g. industry, production size, number of employees, turnover, expenditures (%) in digital technology/innovation on the overall sales, firm's age and location).

In more detail, to assess the extent to which respondent's organization uses or is considering to use the Digital Technologies explored in the second part of the questionnaire (i.e. measurement items concerning the construct of DMC), a control variable has been included in this part (see the following figure):



	not considering at all	slightly considering	considering	strongly considering	currently using
Additive Manufacturing tools (e.g. Rapid Prototyping, 3D Printing, etc.)					
Computer-aided technologies (e.g. CAD, CAE, CAM, etc.)					
Simulation tools (e.g. virtual machines, etc.)					
Big Data Analytics					
Cloud Computing and Digital Platforms					
Collaborative technologies (e.g. discussion forums, audio and video conferencing, enterprise knowledge portals, business directories, etc.)					
Data processing systems and management information system software (e.g. ERP, MES, PLM, etc.)					
Advanced robotics and automation systems (e.g. autonomous and/or collaborative robots, advanced manufacturing systems, cyber-physical systems, etc.)					
Augmented Reality tools (e.g. smart glasses, etc.)					
Mobile devices (e.g. smartphones, tablets, wearables, etc.)					
Internet of Things and smart monitoring systems (e.g. smart sensors, cameras, QR/RFID tags, antennas, microprocessors etc.)					

Fig. 5.3. Capture of the “Use of Techology” Control Variable

As shown in Figure 5.3, respondents were asked to answer on a 5-point Likert scale ranging from (1) “not considering at all” to (5) “currently using”.

Moreover, another control variable was included in this part of the questionnaire to assess the *market dynamism.* For this purpose an existing scale – named “Environmental Dynamism” - has been adapted from the literature on Dynamic Capabilities (Schilke, 2014). Particularly, this variable assesses how fast and unpredictable is the change in the environment where the firm operates in (Miller & Friesen, 1983). The aforementioned variable is represented in table 5.8.

MARKET DYNAMISM		
Item	**Action**	**Reference**
The modes of production/service change often and in a major way	Unchanged	Schilke (2014) α =0.81
The environmental demands on us are constantly changing	Unchanged	
Marketing practices in our industry are constantly changing	Unchanged	
Environmental changes in our industry are unpredictable	Unchanged	
In our environment, new business models evolve frequently	Unchanged	

Table 5.8. Environmental Dynamism

In this case, respondents were asked to express their degree of agreement on a 5-point Likert scale ranging from (1) "strongly disagree" to (5) "strongly agree".

5.6 Chapter Summary

This chapter outlines the design, development and validation of the research instrument. First, the development of the initial pool of items used in this research has been described. This was followed by the detailed description of measurement purification procedures through several rounds of expert review. Next, the web-based questionnaire survey design and pre-test phases were reported, while the last section portrayed the final refinement of the scales, by presenting a summary of the revised measurement items in relation to their constructs and dimensions of origin, consistent with the research model.

In the next chapter the main study, data analysis and final results are presented.

6. Chapter VI: Data Collection and Analysis

6.1 Introduction

Once the research instrument was fully developed, the next step was to test the theoretical model using a large scale survey. Therefore, the purpose of this chapter is to describe the results of the web-based survey as well as to test the conceptual research model and associated hypotheses.

While doing so, this chapter is crucial to address the main research question reported below:

RQ: *What are the factors that drive the development of digital manufacturing capabilities (DMC) and to what extent does it affect organizational performance?*

At the same time, statistical analyses of the data gathered via the web-based survey, by testing the mediation model (further explained in depth on section 6.7) and its relevant hypotheses presented in Chapter III (summarised on section 3.2.4), allow the researcher to fully achieve the last two research objectives:

RO2: *Explore what are the factors that drive the development of Digital Manufacturing Capabilities*

and

RO3: *Understand and assess the extent to which dynamic and digital manufacturing capabilities affect organizational performance.*

The reminder of this chapter is organized as follows: first, the details concerning the main survey, such as data collection procedure and sample adequacy are presented. This is followed by an in-depth data analysis of the results and the actual evaluation of the research model - also in the refined version (containing control variables in addition to the model variables) - through the PLS-SEM approach.

6.2 Data Collection Procedure

As discussed in the previous chapters, the population of interest in this research comprises professionals and companies' managers operating in the manufacturing industry.

The goal in this stage was to gather a large sample of participants working for the abovementioned organizations, in a variety of industries within the manufacturing settings, and possessing a wide range of work tasks (e.g. senior managers, consultants, technical responsible, etc.) (Göritz, 2006; Hinkin, 1998; Klassen & Jacobs, 2001; Pinsonneault & Kraemer, 1993; Shannon et al. 2002; Simsek & Veiga, 2000).

Invitations with a link to the questionnaire were strategically transmitted through the following channels:

- E-mails
- Professional Social media accounts (LinkedIn, Facebook, etc.), through a specific article – both in English and Italian - as an introduction to the online survey link (respectively in English and Italian version).

In the introductory message to the Survey questionnaire, as well as in the email sent to invite people to participate in the survey, it was highlighted that only professionals working for the manufacturing sector were invited to take part in the investigation. Therefore, only people from manufacturing companies or external professionals working in this sector completed the online survey.

Contacts of the participants to the online survey were retrieved throughout the following networks and databases:

- **Adaci** = Italian Association of Purchasing &Supply Management (1000 members), founder member of the International Federation of Purchasing and Supply chain Management (200.000 members);
- **Unindustria Lazio** = Association of Industries of the cities of Rome, Frosinone, Latina, Rieti and Viterbo, in the Lazio region;
- **Confindustria** = General Confederation of Italian Industries;
- **Federmanager** = Italian Association of Industrial Managers;
- **AIDA-Amadeus Databases**: large databases containing a comprehensive listing of firms; the search was based on specific codes that classify economic activities. In more detail, the classification of economic activities in Italy is based on several specific business codes called "Codici ATECO 2007". In particular, for the Manufacturing Industry, the researcher used the codes C 10-33, as reported on ISTAT website[4]. Contact data for 1,200 firms representative of this grouping were obtained.

The sampling strategy was conducted commencing with convenience sampling (inviting colleagues and researchers network to distribute the online survey link), snowball sampling (for those initially invited to distribute the link to other colleagues/collaborators) and purposive sampling (directly contacting participants respecting the eligibility criteria met through the survey introduction).
The next section will present descriptive statistics concerning the sample.

[4] http://www3.istat.it/strumenti/definizioni/ateco/ateco.html?versione=2007.3&codice=C

6.3 Measures and Scales

This section reports schematically the scales' list of the conceptual research model (see table 6.1). Their analyses are described in the sections concerning reliability assessments and factor analyses.

Construct	Scale	N of Items	Measure
HODC	DFR	7	Five-point Likert scale anchors: from (1) "strongly disagree" to (5) "strongly agree"
	DHR	5	
	TMS	5	
	AIT	4	
	SAR	4	
	IC	4	
	CL	5	
	DM	8	
DMC	Dig_Inn_D&D	6	Five-point Likert scale anchors: from (1) "never" to (5) "always".
	Dig_Inn_Man	10	
	Dig_Inn_Prod	6	
(Firm's) Performance	Per_Inn_Perf	12	Five-point Likert scale from (1) "very low" to (5) "very high"
	Per_Fin_Perf	6	Five-point Likert scale from (1)"strongly disagree" to (5)"strongly agree"
	Per_Mkt_Perf	3	

Table 6.1. Model's scales

6.4 Sample Adequacy and Statistics

A total of 110 respondents, both Italian and from several other countries, participated in the aforementioned digital transformation online survey. The sample resulted adequate for PLS analysis. Indeed, It satisfied the heuristic that the sample size has to be at least 10 times the largest number of structural paths directed at any particular latent construct in the structural model (Hair et al., 2011; Subramani, 2004). In the present study, the largest number of paths to any construct in the research model is ten. This count includes also the paths from the four control variables that will be shown in section 6.7.2.2.

In addition, other heuristics are respected by the present sample. First, Comrey and Lee (1992) consider acceptable samples ranging from 100 cases, and counting at least 5 cases for each observed variable (Comrey & Lee, 1992). Moreover, recent studies have shown that the best results are obtained having an higher ratio between the number of variables and the number of factors, as it will be demonstrated in the section about metrical properties (Barbaranelli, 2007; MacCallum, Widaman, Zhang, & Hong, 1999).
These evidences meant that the survey sample was sufficient in size for quantitative analysis.

6.4.1 Respondent Profile

Within the total of respondents, 21 people (19.10% of the sample) refused to complete the questionnaire part concerning socio-demographic questions (e.g., gender, age, role and position within the organization) and firm's characteristics (e.g. industry, firm's size, firm's age, etc.). These questions were kept as optional in order to respect the anonymous nature of the questionnaire. The remaining participants (89 people, 80.90% of the sample) fully completed the questionnaire providing the aforementioned information. Thus, the descriptive statistics presented in the tables above, will refer to the latter.

The sample was mostly composed of males (84%) and the average age was 47 years old (50% of the sample was between 36 and 50 years old, and a further 28% between 51 and 60). This datum is explained by the high value of tenure characterizing the participants, that will be presented below.

Concerning the role within the organization, almost 43 percent of participants were managers, while an overall 28 percent were senior officers - by considering together Top-ranking executive and Director/President categories (e.g. titles such as CEO, CIO, Director, President/Vice president, Head etc.). Particularly, within the Director/President category (21.35%), many respondents resulted Head of Procurement. The "Responsible" category (13.5% of the sample) includes different figures as follows: Engineer and Technical/System responsible, sales responsible, finance responsible, etc.

About the years of experience within the same organization in which respondents are actually working, it was recorded an high average tenure of almost 13 Years (12,75).

Additionally, respondents came from several different business areas. The majority of the sample works in the Procurement area (32.6%), Manufacturing (18%), Marketing &Sales (11.2%) or Service and Support (10.1%). In the "other" category were indicated several different areas, among which Business Process Management and Supply Chain Management. The remaining areas had a range lower than 10% of the online survey sample.

The abovementioned information are shown in table 6.2.

SOCIO-DEMOGRAPHICS			
Dimension	**Category**	**N**	**%**
Gender	Male	75	84.27
	Female	14	15.73
	Tot	89	100
Age	>30	7	7.87
	30-35	5	5.62
	36-50	45	50.56
	51-60	25	28.09
	>60	7	7.87
	Tot	89	100
Role (within the Organization)	Research Scientist	1	1.12
	Consultant/Auditor	2	2.25
	Analyst	2	2.25
	Top-ranking Executive	6	6.74
	Buyer	9	10.11
	Responsible	12	13.48
	Director/President	19	21.35
	Manager	38	42.70
	Tot	89	100
Position (within the Organization)	Finance	2	2.25
	R&D	3	3.37
	IT	8	8.99
	Service and Support	9	10.11
	Marketing and Sales	10	11.24
	Manufacturing	16	17.98
	Procurement	29	32.58
	Other	9	10.11
	Tot	89	100

Table 6.2. Sample Socio-demographic Descriptive Statistics

6.4.2 Firm Profile

As indicated in table 6.3, the sample consisted of well-established firms characterized by an average firm age of 46.5 years and a percentage of 68.5 percent of them with over 30 years of operation.

The study population comprised firms with a number of employees over 250 for the 70 percent (25.9% had more than 10000 employees), operating in a wide range of industries, such as *Rubber and miscellaneous plastic products, Industrial and commercial machinery, Food and Beverage, Packaging and Logistics equipment, Automotive, Apparel and other finished products garments* (i.e. sports equipment, fashion, etc.) and others. Over 65 percent of the companies had annual sales over €50 million, with only 7.9 percent of the sample below €2 million. This statistical evidence is interesting, considering that only 22.5 percent of the sample indicated their production within the mass production category, whereas 23.6 percent indicated a custom production and 30 percent of the sample was characterized by both custom and batch productions.

Lastly, most of the respondents (74.2%) worked for firms operating in Italy, mainly in the north of the country (33.7% of the sample), with a 25.9 percent of respondents working for firms operating abroad.

FIRM'S CHARACTERISTICS		N	%
N of Employees	<10	5	5.6
	10-49	8	9.0
	50-249	14	15.7
	250 – 5000	34	38.2
	>5000-10000	5	5.6
	>10000	23	25.9
Total		89	100
TURNOVER (EUR)	<2 million	7	7.9
	2 - 10 million	8	9.0
	11 - 50 million	14	15.7
	> 50 million	60	67.4
Total		89	100
EXPENDITURES (%) in digital technologies/innovation on the overall sales	0%	1	1.2
	<10%	63	70.8
	10%-15%	16	18.0
	>15%	9	10.0
Total		89	100
FIRM'S AGE	<10	6	6.7
	10 - <30	22	24.7
	30 - <50	21	23.6
	50 - <70	19	21.3
	70 - <90	10	11.2
	90 - >100	11	12.4
Total		89	100
COUNTRY	Abroad - Europe	8	9.0
	Abroad – Rest of the World	15	16.9
	Italy - South/Islands	16	18.0
	Italy - Center	20	22.5
	Italy - North	30	33.7
Total		89	100
INDUSTRY	Aviation	1	0.9
	Furniture and fixtures	1	0.9
	Other transportation means and equipment	2	1.8
	Telecommunication and Cyber- Security Systems	3	2.7
	Electrical equipment and non-electric home appliances	4	3.6
	Fabricated metal products (excluding machinery and equipment)	5	4.5
	Chemical and Pharmaceutical Products	6	5.5
	Computer, Electronic and other electrical/optic equipment	9	8.2
	Apparel and other finished products	10	9.1
	Automotive	10	9.1
	Packaging and Logistics equipment	10	9.1
	Food and Beverage	13	11.8
	Industrial and commercial machinery	13	11.8
	Rubber and miscellaneous plastic products	13	11.8
	Other	10	9.1

Total[5]		110	100
PRODUCTION SIZE	Batch Production	16	18.0
	Mass Production	20	22.5
	Custom Production	21	23.6
	Custom and Batch Production	27	30.3
	Other	5	5.6
Total		89	100

Table 6.3. Firm Sample Descriptive Statistics

At the question "*Please indicate the extent to which your organization uses or is considering to use the following Digital Technologies*" - considering the key digital technologies applications enablers of the digital transformation - high percentage of respondents indicated that applications such as *data processing and management information system software* (58,43%), *mobile devices* (55%), *computer-aided technologies* (41.57%), *collaborative technologies* (40.45%), as well as *cloud computing and digital platforms* (34.83%) are already available and used by the firm they work for. While, on the one hand, *additive manufacturing tools* overall recorded homogeneous responses about firms both not considering (32.58%) and considering/currently using them (respectively 24.72% and 19.10%); on the other hand, 43,82% of participants reported the complete lack of consideration at the moment for *augmented reality tools.* Finally, concerning *big data analytics*, the majority of the sample (70.8% by adding the last three categories) indicated that firms are at least considering or currently using them. Table 6.4 illustrates absolute frequencies and percentages of use concerning these digital technology applications.

[5] The total is 110 since some respondents indicated more than one industry for each firm

Digital technology Application	Frequency of Use									
	Not considering at all		Slightly considering		Considering		Strongly considering		Currently using	
	F	%	F	%	F	%	F	%	F	%
Additive Manufacturing tools (e.g. Rapid Prototyping. 3D Printing. etc.)	29	32.58	12	13.48	22	24.72	9	10.11	17	19.10
Computer-aided technologies (e.g. CAD. CAE. CAM. etc.)	13	14.61	7	7.87	18	20.22	14	15.73	37	41.57
Simulation tools (e.g. virtual machines. etc.)	20	22.47	13	14.61	17	19.10	15	16.85	24	26.97
Big Data Analytics	13	14.61	13	14.61	24	26.97	16	17.98	23	25.84
Cloud Computing and Digital Platforms	8	8.99	11	12.36	19	21.35	20	22.47	31	34.83
Collaborative technologies (e.g. discussion forums. audio and video conferencing. enterprise knowledge portals. business directories. etc.)	6	6.74	7	7.87	20	22.47	20	22.47	36	40.45
Data processing systems and management information system software (e.g. ERP. MES. PLM. etc.)	4	4.49	5	5.62	13	14.61	15	16.85	52	58.43
Advanced robotics and automation systems (e.g. autonomous and/or collaborative robots. advanced manufacturing systems. cyber-physical systems. etc.)	24	26.97	14	15.73	12	13.48	16	17.98	23	25.84
Augmented Reality tools (e.g. smart glasses. etc.)	39	43.82	16	17.98	16	17.98	12	13.48	6	6.74
Mobile devices (e.g. smartphones. tablets. wearables. etc.)	4	4.49	5	5.62	14	15.73	17	19.10	49	55.06
Internet of Things and smart monitoring systems (e.g. smart sensors. cameras. QR/RFID tags. antennas. microprocessors etc.)	15	16.85	12	13.48	13	14.61	20	22.47	29	32.58
Total	89	100	89	100	89	100	89	100	89	100

Table 6.4. Use of Digital Technology Applications by Sample Firms

6.5 Metrological Properties of the Items' Scales

6.5.1 Reliability Assessment

Reliability measures the degree of correlation between items within an individual construct (Straub et al., 2004). Straub (1989) points out that reliability refers to the extent to which the respondent can answer the same questions or close approximations in the same way each time (Straub, 1989). In other words, it evaluates consistency and accuracy. Therefore, as part of measurement validity, reliability was tested to ensure the scales' items were consistent and accurate (Hinkin, 1998; Straub, 1989; Venkatesh et al., 2013). While it may be calculated in different ways, the most commonly accepted measure in field studies is internal consistency reliability using Cronbach's α (Cronbach, 1971; Hinkin, 1998).

In more detail, the Cronbach's alpha for each construct was measured to seek internal consistency – namely, to what extent does a group of items capture the same phenomenon. A reliability alpha of 0.70 is generally suggested, but for exploratory research a score of 0.60 is also considered acceptable (Moore & Benbasat, 1991; Nunnally, 1978; Straub et al., 2004). Thus, since this research was exploratory and developed new items, a Cronbach's alpha of 0.60 was set as the lower limit. In addition, the Cronbach's alpha if item deleted was assessed to further indicate the potential relevance of each item.

In addition to the Cronbach's alpha, the item-total correlation was assessed. It indicates how the overall items correlate. Referring to the relevant literature, the score for this needs to be over 0.30 (Field, 2013).

Table 6.5 shows that both Cronbach's alpha and item-total correlation values of the instrument measurement resulted largely greater than their minimum accepted thresholds mentioned above.

HODC – 42 Items Cronbach's α=0.977		
Item	Item-Total Correlation	Cronbach's α if Item Deleted
DFR1	0.741	0.977
DFR2	0.745	0.977
DFR3	0.724	0.977
DFR4	0.800	0.976
DFR5	0.749	0.977
DFR6	0.786	0.977
DFR7	0.740	0.977
DHR1	0.641	0.977
DHR2	0.724	0.977
DHR3	0.620	0.977
DHR4	0.611	0.977
DHR5	0.724	0.977
TMS1	0.823	0.976
TMS2	0.828	0.976
TMS3	0.752	0.977
TMS4	0.747	0.977
TMS5	0.804	0.976
AIT1	0.630	0.977
AIT2	0.635	0.977
AIT3	0.712	0.977
AIT4	0.649	0.977
SAR1	0.544	0.977
SAR2	0.362	0.978
SAR3	0.266	0.978
SAR4	0.619	0.977
IC1	0.755	0.977
IC2	0.589	0.977
IC3	0.772	0.977
IC4	0.688	0.977
CL1	0.689	0.977
CL2	0.741	0.977
CL3	0.705	0.977
CL4	0.762	0.977
CL5	0.718	0.977
DM1	0.719	0.977
DM2	0.769	0.977
DM3	0.775	0.977
DM4	0.782	0.977
DM5	0.775	0.977
DM6	0.710	0.977
DM7	0.806	0.976
DM8	0.750	0.977

DMC – 22 Items Cronbach's α=0.936		
Item	Item-Total Correlation	Cronbach's α if Item Deleted
Dig_Inn_D&D1	0.477	0.935
Dig_Inn_D&D2	0.686	0.931
Dig_Inn_D&D3	0.561	0.934
Dig_Inn_D&D4	0.755	0.930
Dig_Inn_D&D5	0.620	0.933
Dig_Inn_D&D6	0.527	0.934
Dig_Inn_Man1	0.583	0.933
Dig_Inn_Man2	0.526	0.934
Dig_Inn_Man3	0.751	0.930
Dig_Inn_Man4	0.711	0.931
Dig_Inn_Man5	0.483	0.935
Dig_Inn_Man6	0.535	0.934
Dig_Inn_Man7	0.647	0.932
Dig_Inn_Man8	0.717	0.931
Dig_Inn_Man9	0.534	0.934
Dig_Inn_Man10	0.560	0.934
Dig_Inn_Prod1	0.578	0.933
Dig_Inn_Prod2	0.571	0.933
Dig_Inn_Prod3	0.727	0.931
Dig_Inn_Prod4	0.729	0.931
Dig_Inn_Prod5	0.581	0.933
Dig_Inn_Prod6	0.557	0.934

PERFORMANCE – 21 Items Cronbach's α=0.960		
Perc_Inn_Perf1	0.753	0.958
Perc_Inn_Perf2	0.747	0.958
Perc_Inn_Perf3	0.851	0.957
Perc_Inn_Perf4	0.800	0.958
Perc_Inn_Perf5	0.780	0.958
Perc_Inn_Perf6	0.659	0.959
Perc_Inn_Perf7	0.800	0.958
Perc_Inn_Perf8	0.730	0.958
Perc_Inn_Perf9	0.680	0.959
Perc_Inn_Perf10	0.771	0.958
Perc_Inn_Perf11	0.781	0.958
Perc_Inn_Perf12	0.712	0.959
Perc_Fin_Perf1	0.693	0.959
Perc_Fin_Perf2	0.694	0.959
Perc_Fin_Perf3	0.707	0.959
Perc_Fin_Perf4	0.713	0.959
Perc_Fin_Perf5	0.684	0.959
Perc_Fin_Perf6	0.726	0.959
Perc_Mkt_Perf1	0.716	0.959
Perc_Mkt_Perf2	0.469	0.961
Perc_Mkt_Perf3	0.650	0.959

Table 6.5. Reliability Assessment of the Constructs Measures

6.5.2 Exploratory Factor Analysis (EFA)

In addition to the reliability assessment described so far, in order to investigate the metrological characteristics of the items reflecting the structure of the instrument described in the previous chapter, in the following sub-sections both an explorative factor analysis (EFA; principal component as estimator) and a reliability analysis were conducted for each scale[6]. To assess the reliability of the survey instrument and seek its consistency and accuracy was used the IBM SPSS software.

Exploratory factor analysis (EFA) is a broadly applied statistical technique used to reduce the set of variables into a smaller one. The factor extraction method used in this research was Principal Component Analysis (PCA). This extraction method was used because it allows finding patterns to reduce the factors of the dataset with minimal loss of information (Field, 2013).

To determine the suitability of the data for factor analysis it is essential to analyse the sample size in relation to number of variables, examining the intercorrelations of the entire correlation matrix, using as indicators Bartlett's Test of Sphericity, and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (Field 2009).

The result of Bartlett's Test of Sphericity should be below the 0.05 significance level to indicate that sufficient correlations exist among the items. On the other hand, the Kaiser-Meyer-Olkin test measures the sampling adequacy, which should be greater than 0.50 for a satisfactory factor analysis to proceed (Field, 2009; Hair et al., 1995; Kaiser, 1974).

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.598
Bartlett's Test of Sphericity	Approx. Chi-Square	9819.584
	df	3570
	Sig.	.000

Table 6.6. KMO and Bartlett's Test

Table 6.6 shows that the KMO measure for this sample is acceptable (0.598) and the significance level of the Bartlett's Test (0.00) indicates that the overall intercorrelations assumptions are met. This means that the dataset is suitable for EFA.

Given the investigative nature of EFA, it was decided to run an EFA analysis for each scale of the model. Therefore, prior to run the aforementioned analysis, a KMO and Bartlett's test was calculated for each scale, ranging values from 0.69 to 0.93. Therefore, all the scales resulted suitable for EFA.

[6] A principal component analysis including all the items of the model instrument together was not conducted due to the low ratio between number of participants and number of items.

Furthermore, before running an EFA it is crucial to define the parameters for eventual item deletion. Aligned with the current Management, IS and Psychology literature, this study considered significant for EFA purposes a factor component loadings of 0.60 or higher (Field, 2009; Straub et al., 2004). Overall , the thresholds for the statistical tests were Cronbach's alpha (>0.60), item-total correlation (>0.30), Cronbach's alpha if item deleted (lower than the Cronbach's alpha of the scale). The results for each item are summarised in the following sections, organized by scale.

A further issue is deciding the number of factors to extract. In the literature, there is no agreement concerning the most appropriate way to determine the number of factors to be extracted in an EFA (Conway & Huffcutt, 2003; Hayton, et al., 2004). The most used methods available include Kaiser's "eigenvalues greater than one" rule, scree plot tests, parallel analysis and a priori theory (Field, 2009). As it is recommended that researchers not rely only on a single method (Costello & Osborne, 2005), this study uses a combination of techniques to determine the number of factors to be extracted.

In summary, the following factor extraction rules were implemented for each scale:

- Factor extraction method: Principal Component Analysis (PCA)
- Number of factors to retain: Eingenvalue >1, scree plot analysis and 1 hypothesized factor
- Factor loading threshold: 0.60

Specifically, in the following sub-sections for each scale are presented in detail the metrological properties of the items, including mean, standard deviation, item-total correlation, Cronbach's alpha when a single item was deleted, and factor loadings for the mono-dimensional solution.

6.5.2.1 DFR Scale

As illustrated in Table 6.7, all items of DFR scale resulted in high values of factor loadings in the principal component extracted (as estimated in the EFA), that showed over 70% of explained variance.

Item	Mean	Standard Deviation	Item-total correlation	Cronbach's alpha if item deleted	Factor loadings	Variance explained by the one-factor solution (%)
DFR1	20.97	26.69	.78	.92	.85	70.69
DFR2	20.75	28.13	.78	.92	.84	
DFR3	21.27	27.19	.73	.92	.81	
DFR4	21.14	25.94	.85	.91	.90	
DFR5	21.31	27.08	.76	.92	.83	
DFR6	21.01	26.67	.77	.92	.83	
DFR7	20.98	26.51	.77	.92	.84	

Table 6.7. Metrical Properties of DFR Scale's Items

The next procedure was to deploy the scree plot test (Hair, Anderson et al. 1995). It consists of plotting a graph containing the eigenvalues of the factors and identifying a point on the curve where the decrease of eigenvalues appearing to level off in a more pronounced manner towards the right side of the plot (Hair et al., 1995). Concerning the scree plot of DFR scale, the difference between the first eigenvalue and the others clearly suggested the 1 factor (monodimensional) solution as the best one.

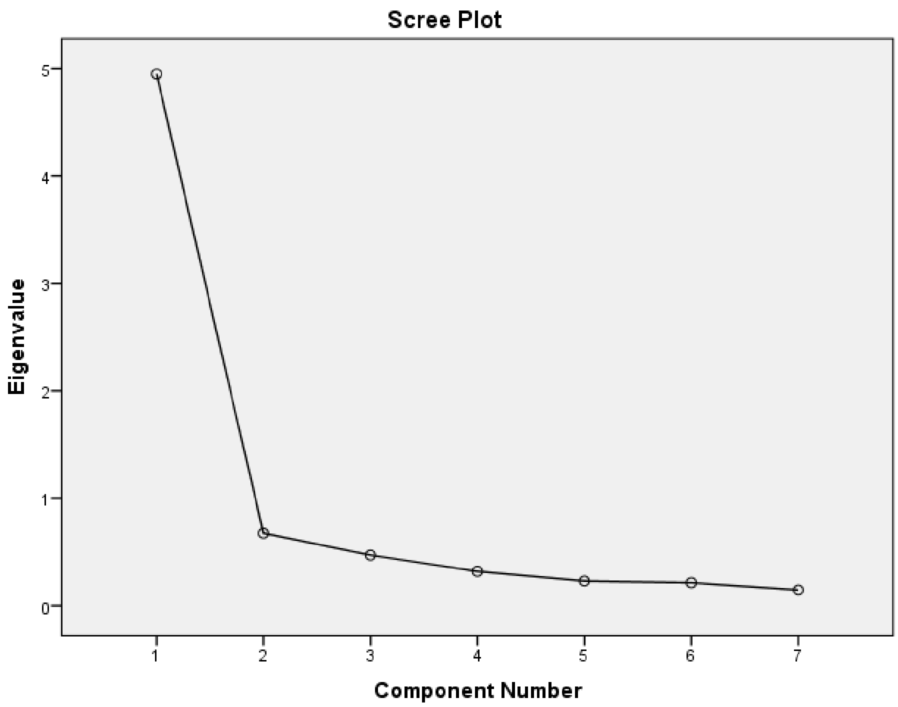


Figure 6.1 DFR Scale's Scree Plot

6.5.2.2 DHR Scale

As illustrated in Table 6.8, all items of DHR scale resulted in high values of factor loadings in the first component extracted (as estimated in the EFA), that showed 68.15% of explained variance.

Item	Mean	Item-total correlation	Cronbach's alpha if item deleted	Factor loadings	Variance explained by the one-factor solution (%)
DHR1	13.54	0.67	0.87	0.79	68.15
DHR2	13.44	0.78	0.84	0.86	
DHR3	13.46	0.77	0.84	0.87	
DHR4	13.40	0.69	0.86	0.80	
DHR5	13.40	0.68	0.87	0.80	

Table 6.8. Metrical Properties of DHR Scale's Items

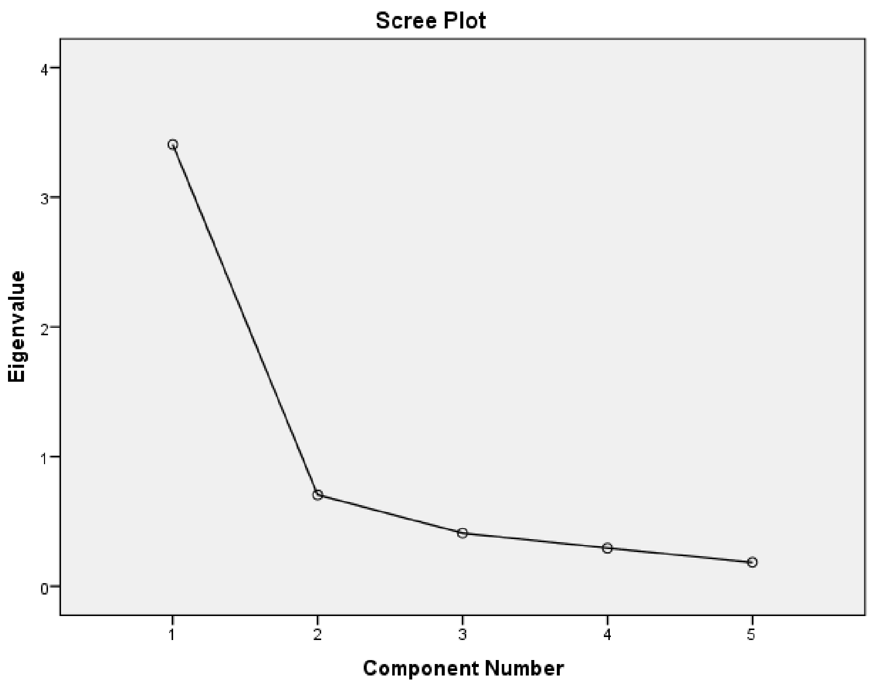


Figure 6.2. DHR Scale's Scree Plot

Figure 6.2 shows the scree plot test of DHR scale, that clearly indicated the 1 factor solution as the best one.

6.5.2.3 TMS Scale

As illustrated in Table 6.9, all items of TMS scale resulted in high values of factor loadings in the first component extracted (as estimated in the EFA), that showed 84.92% of explained variance.

Item	Mean	Item-total correlation	Cronbach's alpha if item deleted	Factor loadings	Variance explained by the one-factor solution (%)
TMS1	13.31	0.89	0.94	0.93	84.92
TMS2	13.18	0.90	0.94	0.94	
TMS3	13.14	0.84	0.95	0.90	
TMS4	13.64	0.86	0.95	0.91	
TMS5	13.50	0.89	0.94	0.93	

Table 6.9. Metrical Properties of TMS Scale's Items

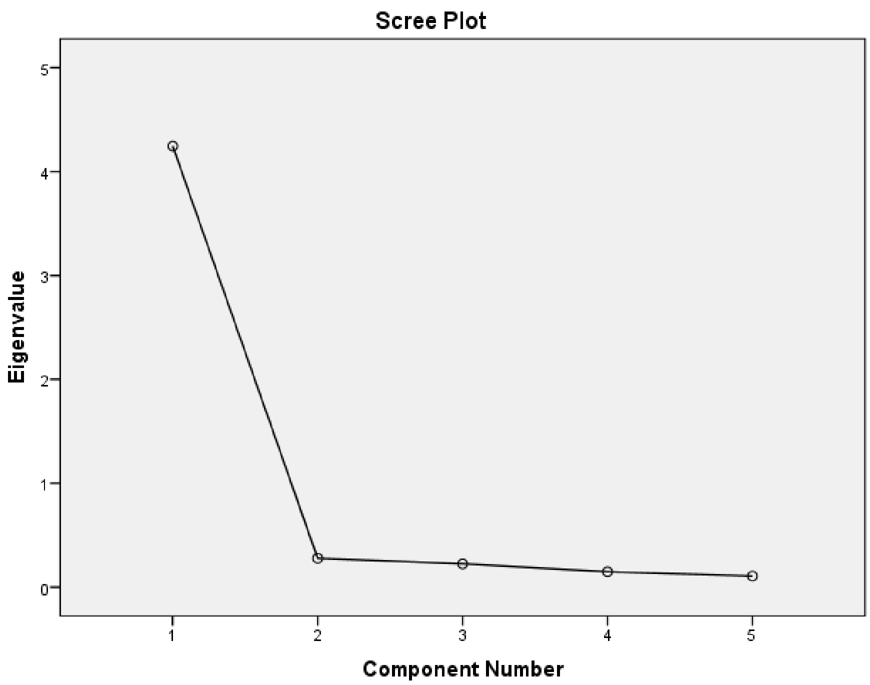


Figure 6.3. TMS Scale's Scree Plot

Figure 6.3 shows the scree plot test of TMS scale, that clearly indicated the 1 factor solution as the best one.

6.5.2.4 AIT Scale

As illustrated in Table 6.10, all items of AIT scale resulted in high values of factor loadings in the first component extracted (as estimated in the EFA), that showed 75,87% of explained variance.

Item	Mean	Item-total correlation	Cronbach's alpha if item deleted	Factor loadings	Variance explained by the one-factor solution (%)
AIT1	9.31	0.74	0.87	0.85	75.87
AIT2	9.35	0.77	0.86	0.88	
AIT3	9.12	0.79	0.85	0.89	
AIT4	9.37	0.76	0.87	0.87	

Table 6.10. Metrical Properties of AIT Scale's Items

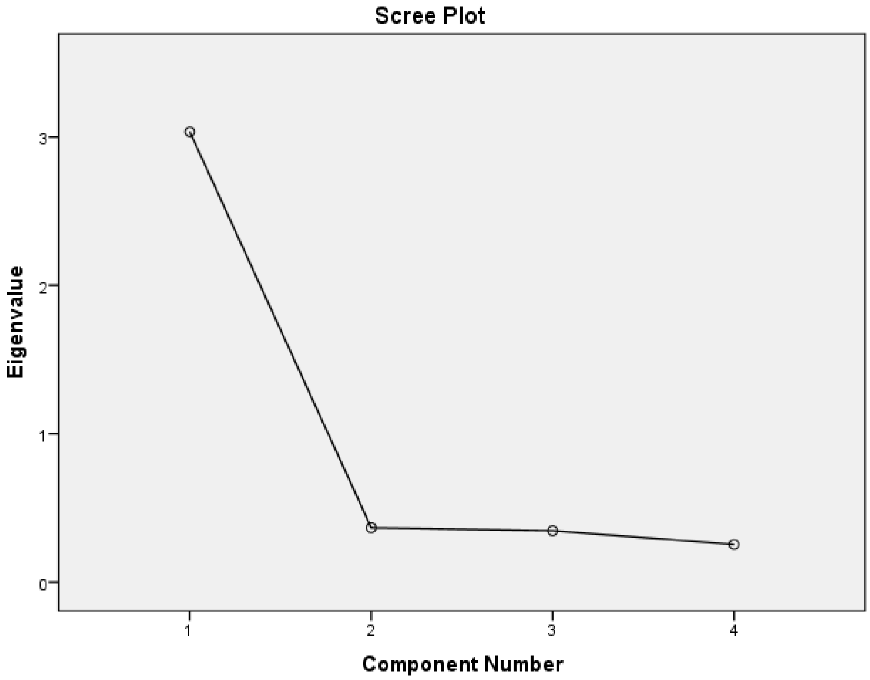


Figure 6.4 AIT Scale's Scree Plot

Figure 6.4 shows the scree plot test of AIT scale, that clearly indicated the 1 factor solution as the best one.

6.5.2.5 SAR Scale

As illustrated in Table 6.11, all items of SAR scale resulted in high values of factor loadings in the first component extracted (as estimated in the EFA), that showed 61,59% of explained variance.

Item	Mean	Item-total correlation	Cronbach's alpha if item deleted	Factor loadings	Variance explained by the one-factor solution (%)
SAR1	9.95	0.52	0.78	0.72	61.59
SAR2	10.46	0.65	0.71	0.82	
SAR3	10.30	0.63	0.72	0.81	
SAR4	10.17	0.61	0.74	0.79	

Table 6.11. Metrical Properties of SAR Scale's Items

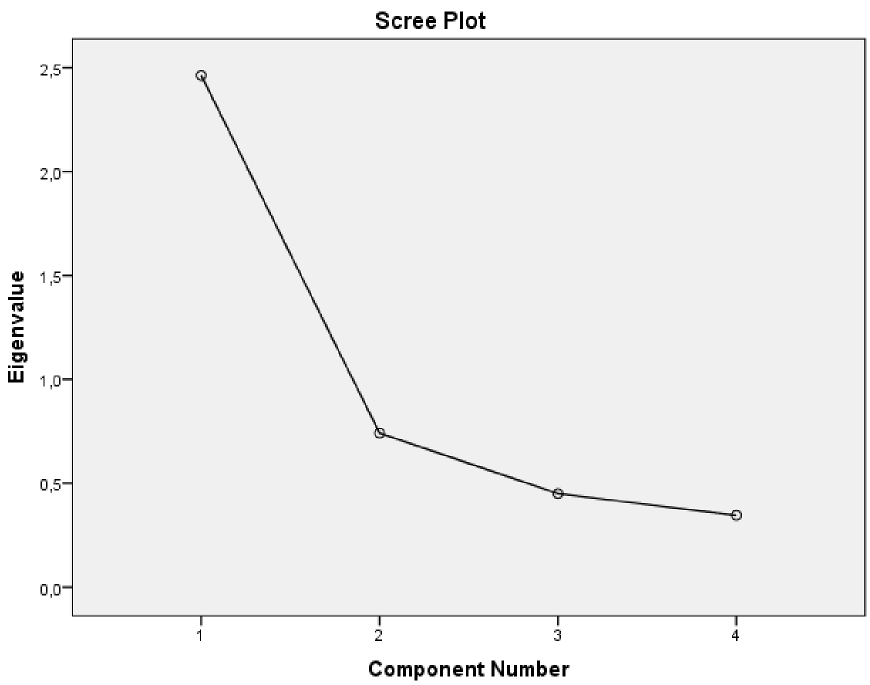


Figure 6.5. SAR Scale's Scree Plot

Figure 6.5 shows the scree plot test of SAR scale, that clearly indicated the 1 factor solution as the best one.

6.5.2.6 IC Scale

As illustrated in Table 6.11, all items of IC scale resulted in high values of factor loadings in the first component extracted (as estimated in the EFA), that showed 76,06% of explained variance.

Item	Mean	Item-total correlation	Cronbach's alpha if item deleted	Factor loadings	Variance explained by the one-factor solution (%)
IC1	11.10	0.76	0.87	0.87	76.06
IC2	11.12	0.71	0.89	0.83	
IC3	11.08	0.86	0.83	0.93	
IC4	10.99	0.75	0.87	0.86	

Table 6.12 Metrical Properties of IC Scale's Items

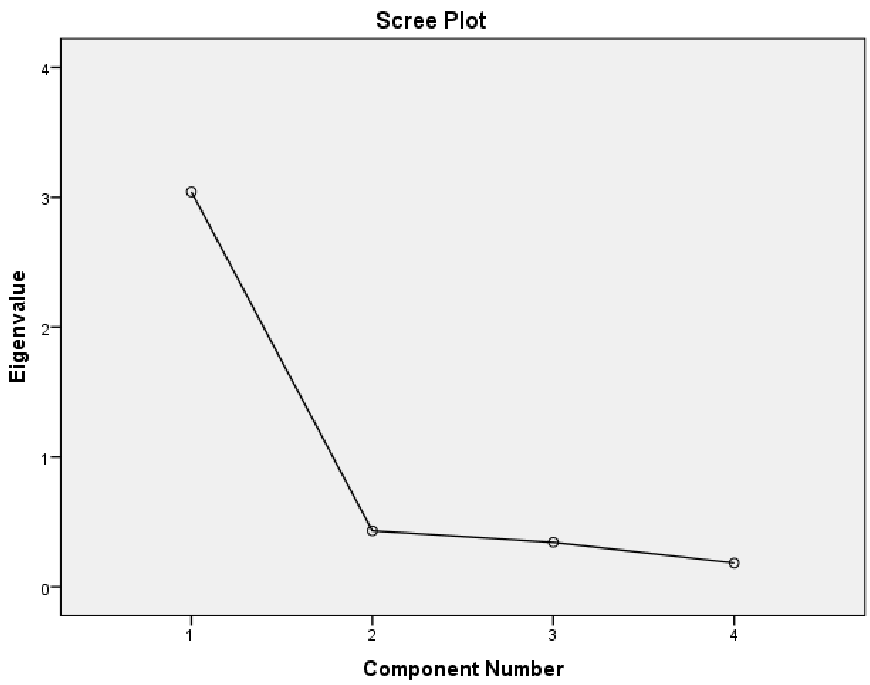


Figure 6.6. IC Scale's Scree Plot

Figure 6.6 shows the scree plot test of IC scale, that clearly indicated the 1 factor solution as the best one.

6.5.2.7 CL Scale

As illustrated in Table 6.13, all items of CL scale resulted in high values of factor loadings in the first component extracted (as estimated in the EFA), that showed 76,34% of explained variance.

Item	Mean	Item-total correlation	Cronbach's alpha if item deleted	Factor loadings	Variance explained by the one-factor solution (%)
CL1	12.85	0.79	0.91	0.86	76.34
CL2	13.08	0.82	0.90	0.89	
CL3	13.24	0.79	0.91	0.87	
CL4	13.03	0.83	0.90	0.89	

Table 6.13. Metrical Properties of CL Scale's Items

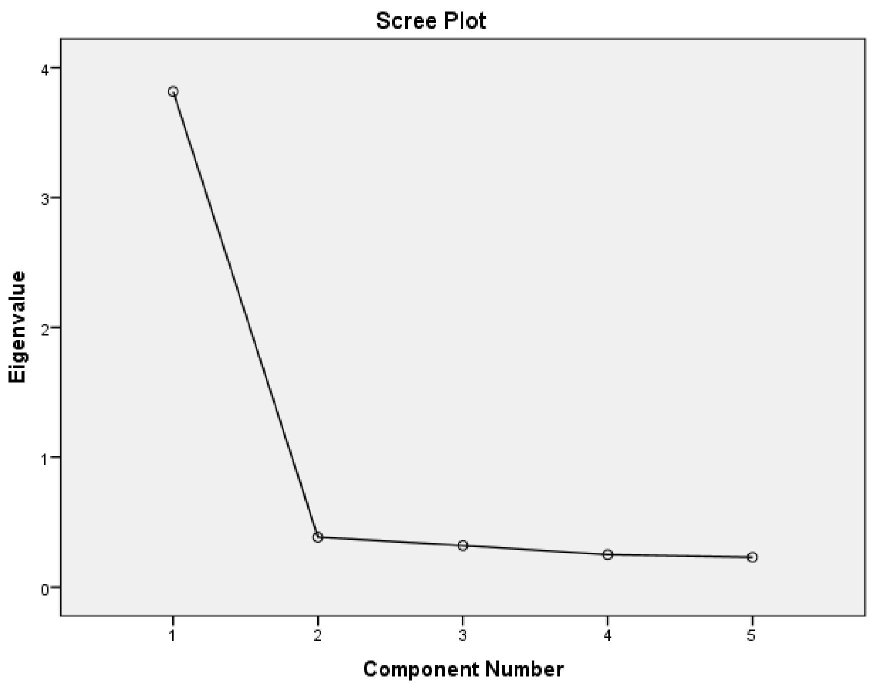


Figure 6.7. CL Scale's Scree Plot

Figure 6.7 shows the scree plot test of CL scale, that clearly indicated the 1 factor solution as the best one.

6.5.2.8 DM Scale

As illustrated in Table 6.14, all items of DM scale resulted in high values of factor loadings in the first component extracted (as estimated in the EFA), that showed 73,15% of explained variance.

Item	Mean	Item-total correlation	Cronbach's alpha if item deleted	Factor loadings	Variance explained by the one-factor solution (%)
DM1	23.58	0.78	0.94	0.83	73.15
DM2	23.25	0.86	0.94	0.90	
DM3	23.03	0.86	0.94	0.90	
DM4	22.95	0.80	0.94	0.85	
DM5	22.95	0.85	0.94	0.89	
DM6	23.36	0.76	0.94	0.82	
DM7	23.20	0.83	0.94	0.87	
DM8	23.87	0.72	0.95	0.77	

Table 6.14 Metrical Properties of DM Scale's Items

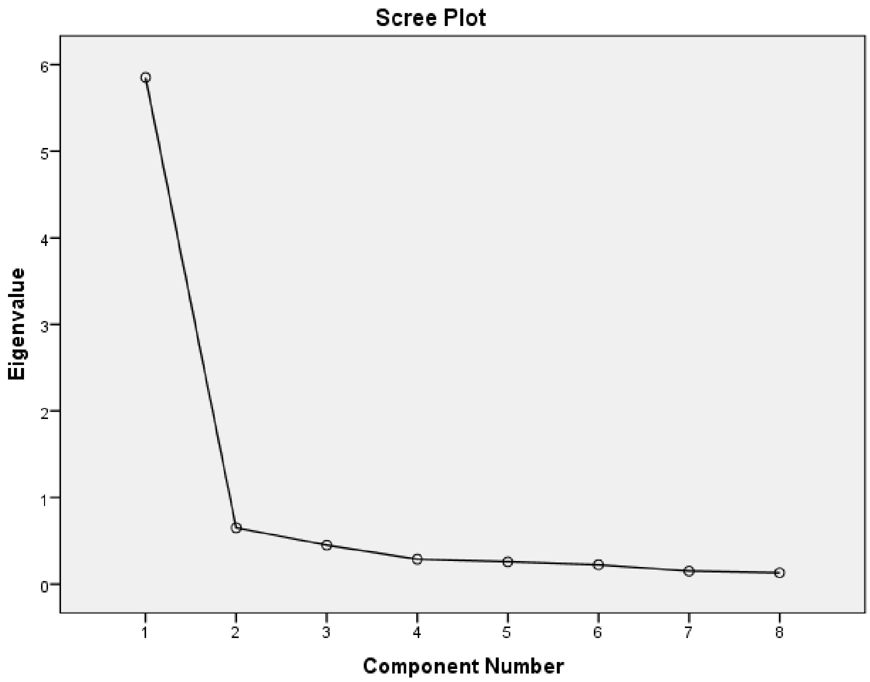


Figure 6.8. DM Scale's Scree Plot

Figure 6.6 shows the scree plot test of DM scale, that clearly indicated the 1 factor solution as the best one.

6.5.2.9 Dig Inn D&D Scale

Concerning this scale, the EFA applied on all the items indicated a two-dimensional solution as the best one (see table and scree plot below). As a result of the EFA, Dig Inn D&D Scale was separated into 2 dimensions. Indeed, as illustrated in the table below (Table 6.15), by applying Kaiser's "eigenvalues greater than one" this scale indicated two components with eigenvalues greater than 1. Moreover, also the scree plot test confirmed the bi-dimensional solution as the most adequate. Therefore, the present scale was split into two sub-scales as indicated in the two following sections.

Total Variance Explained			
Component	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1	3.08	51.35	51.35
2	1.24	20.69	72.04
3	0.55	9.19	81.24
4	0.48	8.00	89.24
5	0.41	6.86	96.10
6	0.23	3.90	100.00
Extraction Method: Principal Component Analysis.			

Table 6.15. Variance Explained by Components

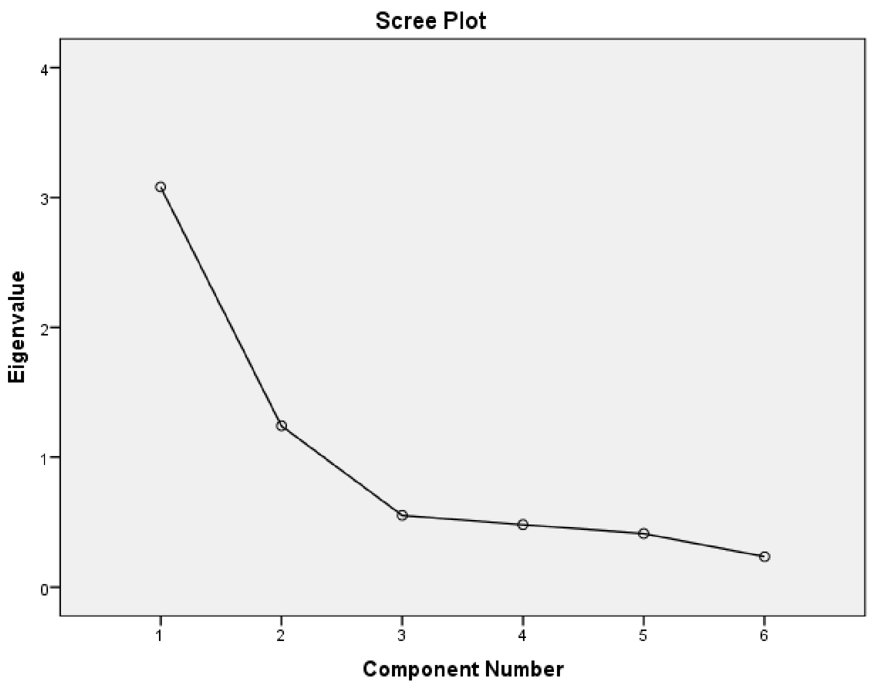


Figure 6.9. D&D Scale's Scree Plot

In particular, based on the factor loadings values of the items (see table 6.16), it was decided to assigned the items in the following manner: from Dig_Inn_D&D1 to Dig_Inn_D&D3 to a scale named "*Dig Inn D&D Hard*"; whereas from Dig_Inn_D&D4 to Dig_Inn_D&D6 to a scale named "*Dig Inn D&D Soft*". These two scales were named based on the items' content, divided into hard and soft tools to represent their functional nature.

Pattern Matrix		
Item	**Component**	
	1	**2**
Dig_Inn_D&D1 - Additive Manufacturing tools (e.g. Rapid Prototyping. 3D Printing, etc.)	0.87	0.12
Dig_Inn_D&D2 - Simulation tools (e.g. virtual machines, etc.)	0.79	-0.14
Dig_Inn_D&D3 - Computer-aided technologies (e.g. CAD, CAE, etc.)	0.81	-0.05
Dig_Inn_D&D4 - Big Data Analytics	0.29	-0.72
Dig_Inn_D&D5 - Cloud Computing Platforms	-0.02	-0.88
Dig_Inn_DnD6 - Collaborative technologies (e.g. discussion forums, audio and video conferencing, enterprise knowledge portals, business directories)	-0.09	-0.86
Extraction Method: Principal Component Analysis.		
Rotation Method: Oblimin with Kaiser Normalization.		

Table 6.16. Factor Loadings Values of the Items

Dig Inn D&D Hard Scale

As illustrated in Table 6.17, all items of Dig Inn D&D Hard scale resulted in high values of factor loadings in the principal component extracted (as estimated in the EFA), that showed 69.70 % of explained variance.

Item	Mean	Item-total correlation	Cronbach's alpha if item deleted	Factor loadings	Variance explained by the one-factor solution (%)
Dig_Inn_D&D_HD1	6.66	0.61	0.72	0.83	69.70
Dig_Inn_D&D_HD2	6.42	0.65	0.67	0.85	
Dig_Inn_D&D_HD3	5.45	0.61	0.72	0.83	

Table 6.17. Metrical Properties of Dig Inn D&D Hard Scale's Items

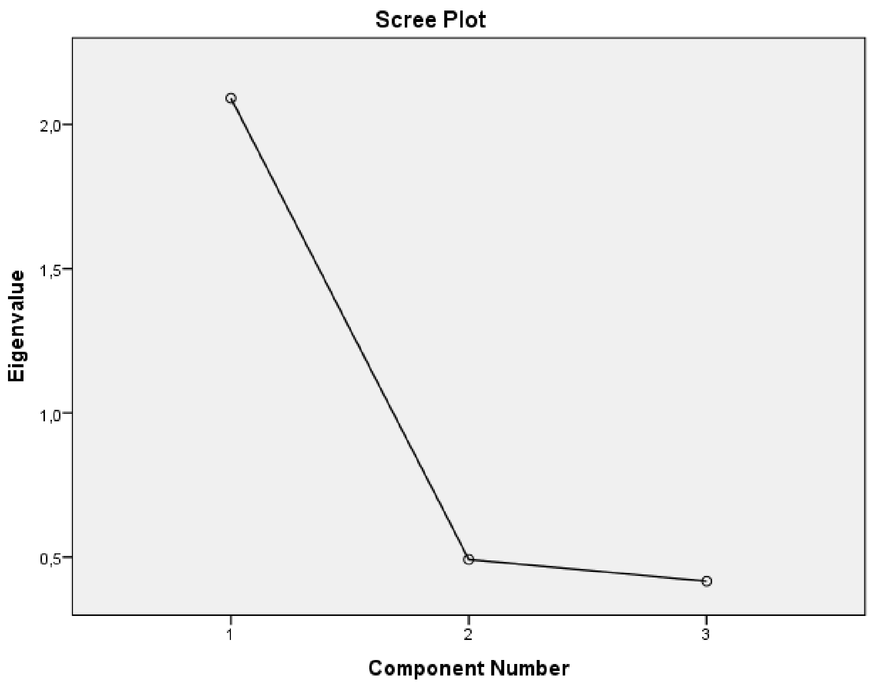


Figure 6.10. Dig Inn D&D Hard Scale's Scree Plot

Figure 6.10 shows the scree plot test of D&D Hard scale, that clearly indicated the 1 factor (i.e. monodimensional) solution as the best one.

Dig Inn D&D Soft Scale

As illustrated in Table 6.18, all items of Dig Inn D&D Soft scale resulted in high values of factor loadings in the first component extracted (as estimated in the EFA), that showed 71,74% of explained variance.

Item	Mean	Item-total correlation	Cronbach's alpha if item deleted	Factor loadings	Variance explained by the one-factor solution (%)
Dig_Inn_D&D_ST1	7.00	0.67	0.71	0.86	71.74
Dig_Inn_D&D_ST2	6.75	0.70	0.68	0.88	
Dig_Inn_D&D_ST3	6.41	0.59	0.79	0.81	

Table 6.18. Metrical Properties of Dig Inn D&D Soft Scale's Items

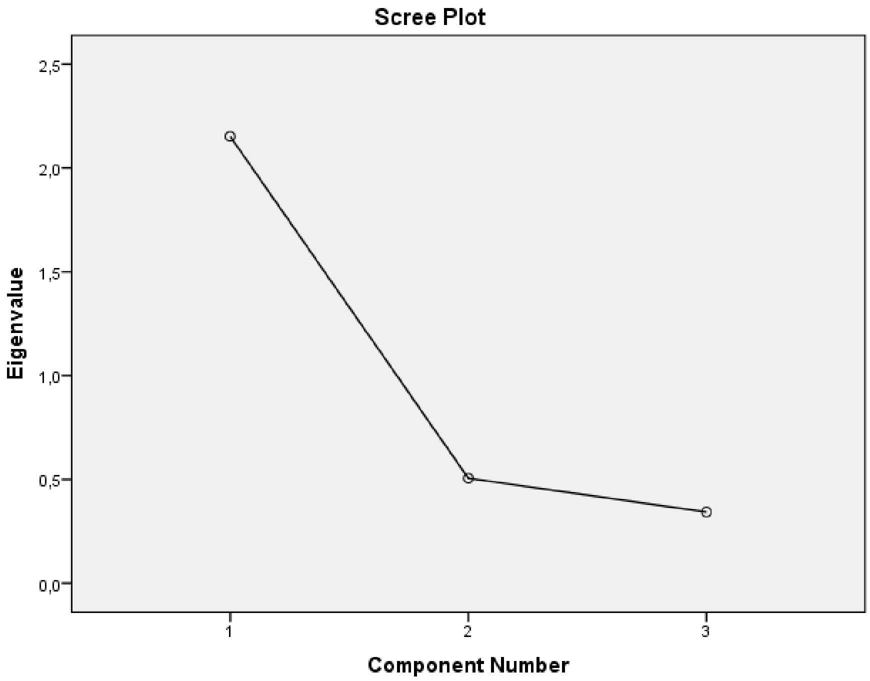


Figure 6.11. Dig Inn D&D Soft Scale's Scree Plot

Figure 6.11 shows the scree plot test of Dig Inn D&D Soft scale, that clearly indicated the 1 factor solution as the best one.

6.5.2.10 Dig Inn Man Scale

As per the previous scale (Dig Inn D&D), after the EFA also Dig Inn Man scale was separated into 2 dimensions. In fact, as illustrated in the table below (Table 6.19), through the application of Kaiser's "eigenvalues greater than one", this scale indicated two components with eigenvalues greater than 1. From the same table it is possible to observe that the percentage of variance explained by the monodimensional solution is lower than 50 percent (48,59 %). Moreover, also the scree plot test confirmed the bi-dimensional solution as the most adequate (see figure 6.12). Therefore, the present scale was split into two sub-scales as indicated in the two following sections.

Total Variance Explained			
Component	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1	4.86	48.59	48.59
2	1.34	13.42	62.00
3	0.88	8.76	70.77
4	0.82	8.20	78.96
5	0.53	5.25	84.21
6	0.46	4.59	88.80
7	0.37	3.72	92.52
8	0.32	3.22	95.74
9	0.24	2.44	98.18
10	0.18	1.82	100.00
Extraction Method: Principal Component Analysis.			

Table 6.19 Variance Explained by Components

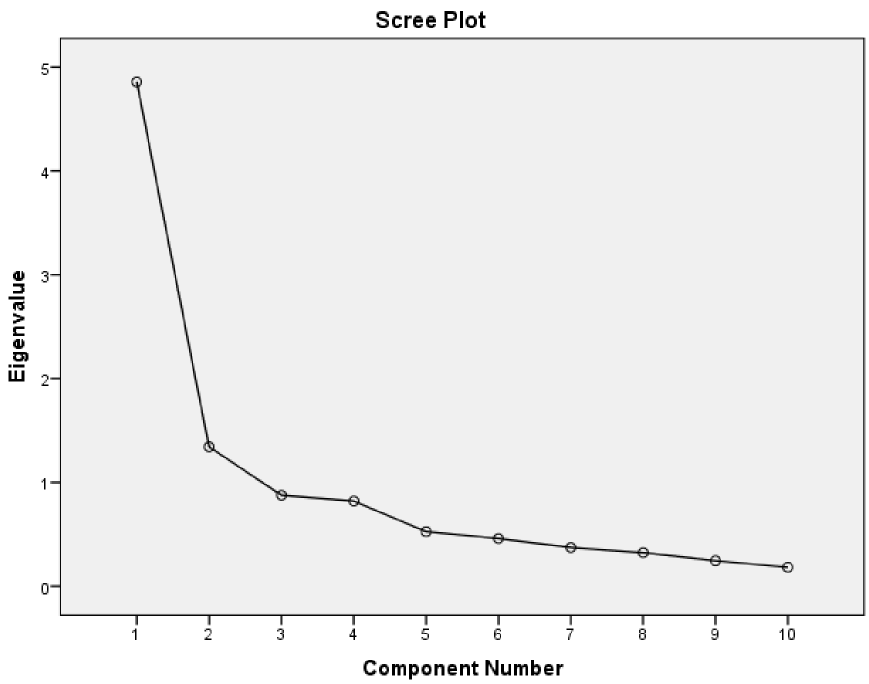


Figure 6.12. Dig Inn Man scale's Scree Plot

In more details, based on the factor loadings values of the items (presented in Table 6.20), it was decided to assigned them in the following manner: Dig_Inn_Man1, Dig_Inn_Man2, Dig_Inn_Man6, Dig_Inn_Man7 and Dig_Inn_Man8 to a scale named "*Dig Inn Man Hard*"; whereas Dig_Inn_Man3, Dig_Inn_Man4, Dig_Inn_Man5, Dig_Inn_Man9, Dig_Inn_Man10, to a scale named "*Dig Inn Man Soft*". These two scales were named based on the items' content, divided into hard and soft tools to reflect their functional nature.

Pattern Matrix		
Item	**Component**	
	1	**2**
Dig_Inn_Man9	**0.92**	-0.16
Dig_Inn_Man10	**0.88**	-0.10
Dig_Inn_Man4	**0.70**	0.18
Dig_Inn_Man5	**0.62**	0.12
Dig_Inn_Man3	**0.59**	0.33
Dig_Inn_Man2	-0.11	**0.86**
Dig_Inn_Man1	-0.05	**0.83**
Dig_Inn_Man7	0.10	**0.74**
Dig_Inn_Man6	0.14	**0.65**
Dig_Inn_Man8	0.43	**0.44**
Extraction Method: Principal Component Analysis.		
Rotation Method: Oblimin with Kaiser Normalization. Rotation converged in 8 iterations		

Table 6.20 Factor Loadings Values of the Items

Dig Inn Man Hard Scale

As illustrated in Table 6.21, all items of Dig Inn Man Hard scale resulted in high values of factor loadings in the first component extracted (as estimated in the EFA), that showed 58,67% of explained variance.

Item	Mean	Item-total correlation	Cronbach's alpha if item deleted	Factor loadings	Variance explained by the one-factor solution (%)
Dig_Inn_Man_HD1	10.74	0.62	0.78	0.83	58.67
Dig_Inn_Man_HD2	9.98	0.59	0.79	0.77	
Dig_Inn_Man_HD6	10.36	0.60	0.79	0.76	
Dig_Inn_Man_HD7	11.08	0.70	0.76	0.75	
Dig_Inn_Man_HD8	10.50	0.57	0.80	0.73	

Table 6.21. Metrical Properties of Dig Inn Man Hard Scale's Items

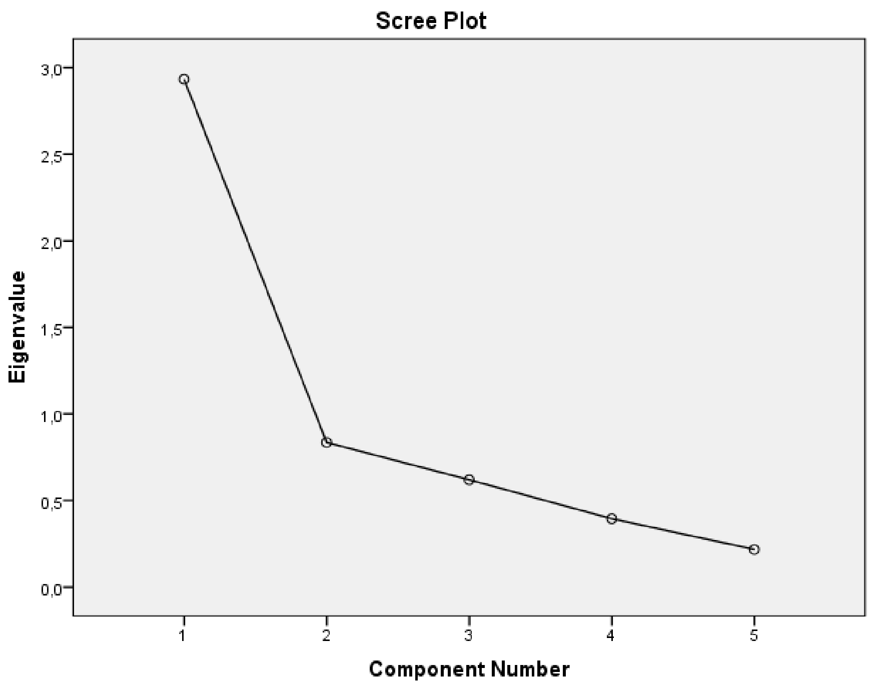


Figure 6.13. Dig Inn Man Hard Scale's Scree Plot

Figure 6.13 shows the scree plot test of Dig Inn Man Hard scale, that clearly indicated the 1 factor solution as the best one.

Dig Inn Man Soft Scale

As illustrated in Table 6.22, all items of Dig Inn Man Hard scale resulted in high values of factor loadings in the first component extracted (as estimated in the EFA), that showed 61,72 % of explained variance.

Item	Mean	Item-total correlation	Cronbach's alpha if item deleted	Factor loadings	Variance explained by the one-factor solution (%)
Dig_Inn_Man_ST3	14.60	0.66	0.81	0.82	61.72
Dig_Inn_Man_ST4	14.46	0.69	0.80	0.82	
Dig_Inn_Man_ST5	13.53	0.53	0.84	0.81	
Dig_Inn_Man_ST9	13.84	0.70	0.80	0.80	
Dig_Inn_Man_ST10	14.09	0.68	0.81	0.68	

Table 6.22 Metrical Properties of Dig Inn Man Soft Scale's Items

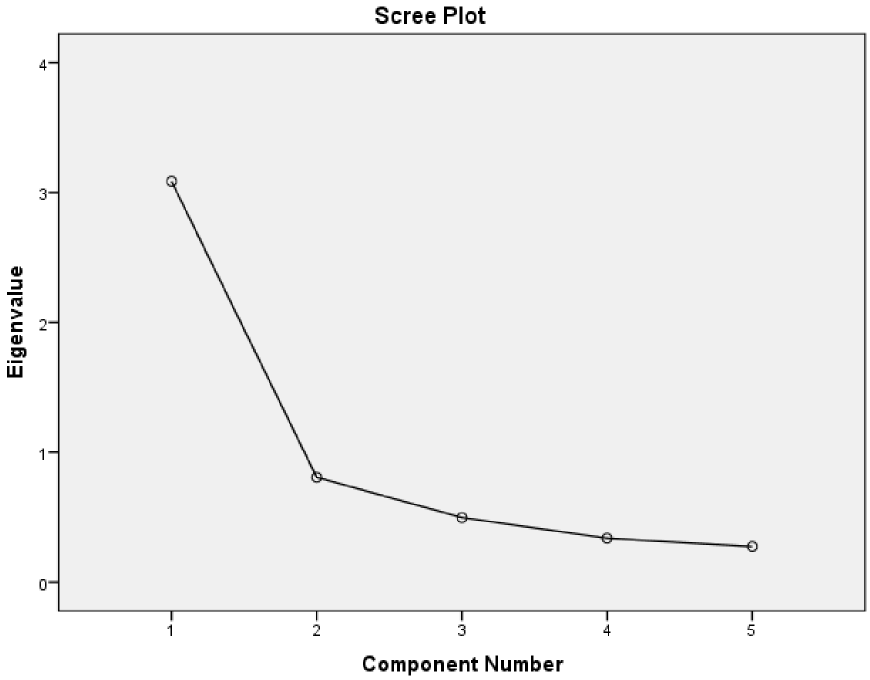


Figure 6.14. Dig Inn Man Soft Scale's Scree Plot

Figure 6.14 shows the scree plot test of Dig Inn Man Soft scale, that clearly indicated the 1 factor solution as the best one.

6.5.2.11 Dig Inn Prod Scale

As illustrated in Table 6.23, all items of Dig Inn Prod scale resulted in high values of factor loadings in the first component extracted (as estimated in the EFA), that showed 70,71 % of explained variance.

Item	Mean	Item-total correlation	Cronbach's alpha if item deleted	Factor loadings	Variance explained by the one-factor solution (%)
Dig_Inn_Prod1	13.15	0.70	0.91	0.79	70.71
Dig_Inn_Prod2	13.28	0.76	0.90	0.83	
Dig_Inn_Prod3	13.18	0.84	0.89	0.90	
Dig_Inn_Prod4	13.28	0.83	0.89	0.89	
Dig_Inn_Prod5	13.19	0.76	0.90	0.84	
Dig_Inn_Prod6	12.70	0.70	0.91	0.79	

Table 6.23 Metrical Properties of Dig Inn Prod Scale's Items

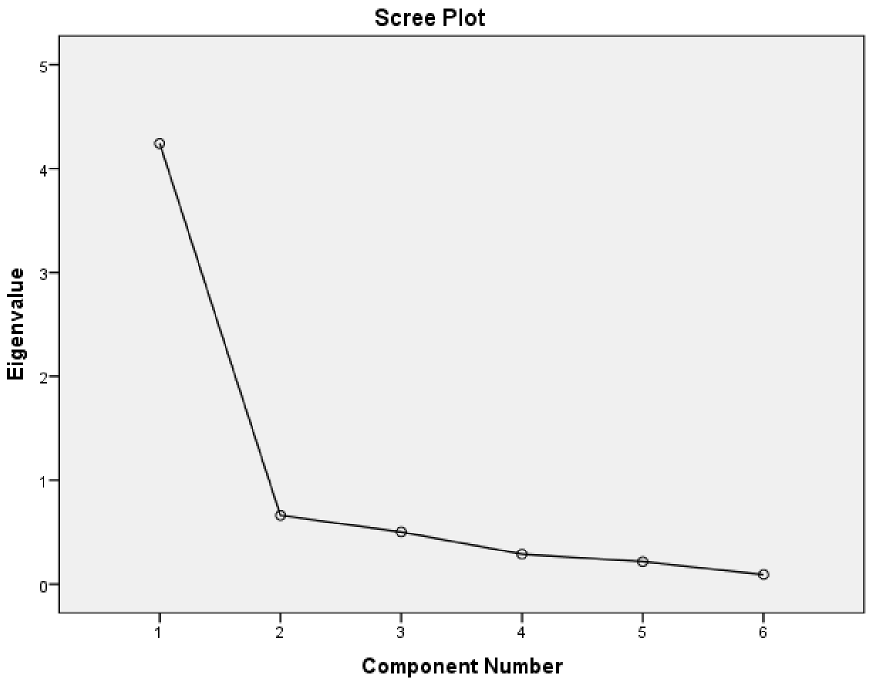


Figure 6.15. Dig Inn Prod Scale's Scree Plot

Figure 6.15 shows the scree plot test of Dig Inn Prod scale, that clearly indicated the 1 factor solution as the best one.

6.5.2.12 Perc Inn Perf Scale

As illustrated in Table 6.23, all items of Perc Inn Perf scale resulted in high values of factor loadings in the first component extracted (as estimated in the EFA), that showed 68,75 % of explained variance.

Item	Mean	Item-total correlation	Cronbach's alpha if item deleted	Factor loadings	Variance explained by the one-factor solution (%)
Perc_Inn_Perf1	33.00	0.77	0.96	0.81	68.75
Perc_Inn_Perf2	32.95	0.76	0.96	0.80	
Perc_Inn_Perf3	32.86	0.88	0.95	0.90	
Perc_Inn_Perf4	32.57	0.82	0.95	0.86	
Perc_Inn_Perf5	32.68	0.85	0.95	0.88	
Perc_Inn_Perf6	32.74	0.69	0.96	0.74	
Perc_Inn_Perf7	32.85	0.80	0.95	0.84	
Perc_Inn_Perf8	32.65	0.76	0.96	0.80	
Perc_Inn_Perf9	32.74	0.75	0.96	0.79	
Perc_Inn_Perf10	32.57	0.84	0.95	0.87	
Perc_Inn_Perf11	32.57	0.84	0.95	0.87	
Perc_Inn_Perf12	33.11	0.75	0.96	0.79	

Table 6.24 Metrical Properties of Perc Inn Perf Scale's Items

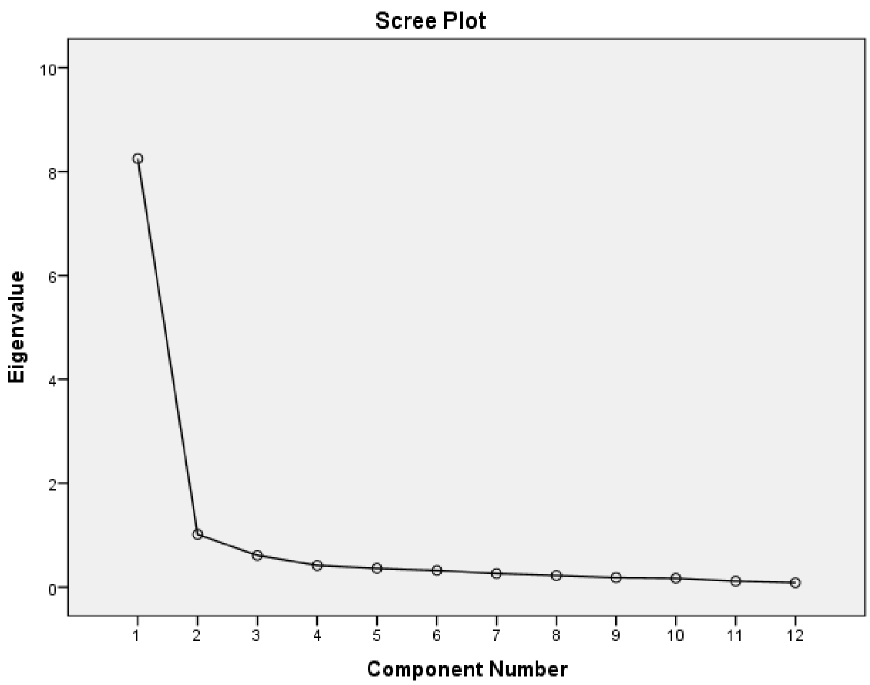


Figure 6.16. Perc Inn Perf Scale's Scree Plot

Figure 6.16 shows the scree plot test of Perc Inn Perf scale, that clearly indicated the 1 factor solution as the best one.

6.5.2.13 Perc Fin Perf Scale

As illustrated in Table 6.25, all items of Perc Fin Perf scale resulted in high values of factor loadings in the first component extracted (as estimated in the EFA), that showed 85.40 % of explained variance.

Item	Mean	Item-total correlation	Cronbach's alpha if item deleted	Factor loadings	Variance explained by the one-factor solution (%)
Perc_Fin_Perf1	15.43	0.90	0.96	0.93	85.40
Perc_Fin_Perf2	15.41	0.91	0.96	0.94	
Perc_Fin_Perf3	15.40	0.89	0.96	0.93	
Perc_Fin_Perf4	15.45	0.91	0.96	0.94	
Perc_Fin_Perf5	15.42	0.91	0.96	0.94	
Perc_Fin_Perf6	15.45	0.81	0.97	0.86	

Table 6.25. Metrical properties of Perc Fin Perf Scale's Items

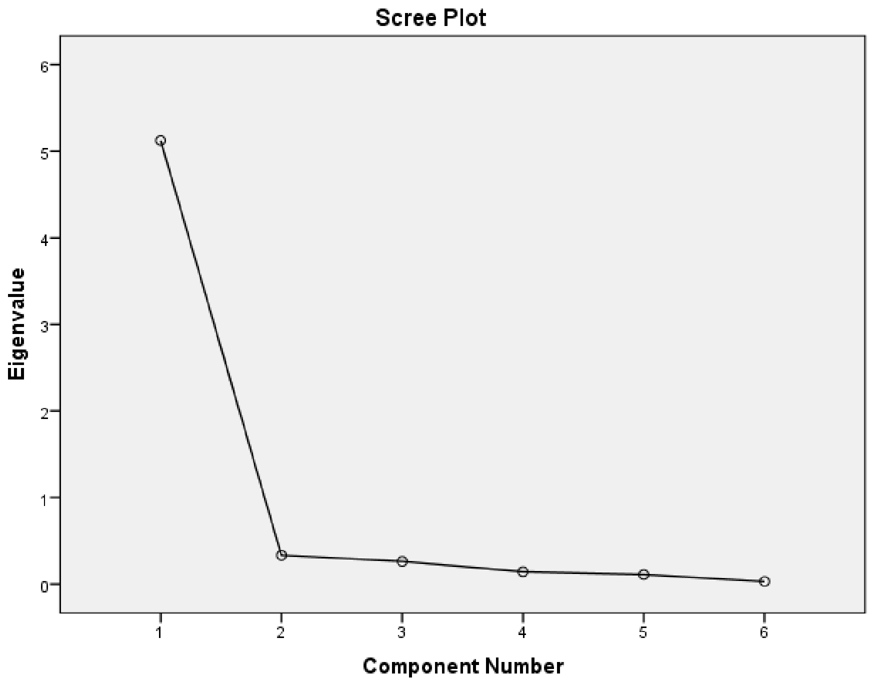


Figure 6.17. Perc Fin Perf Scale's Scree Plot

Figure 6.17 shows the scree plot test of Perc Fin Perf scale, that clearly indicated the 1 factor solution as the best one.

6.5.2.14 Perc Mkt Perf Scale

As illustrated in Table 6.26, all items of Perc Mkt Perf scale resulted in high values of factor loadings in the first component extracted (as estimated in the EFA), that showed 75.06 % of explained variance.

Metrical properties of Perc_Mkt_Perf items					
Item	Mean	Item-total correlation	Cronbach's alpha if item deleted	Factor loadings	Variance explained by the one-factor solution (%)
Perc_Mkt_Perf1	6.97	0.66	0.79	0.85	75.06
Perc_Mkt_Perf2	6.65	0.64	0.81	0.84	
Perc_Mkt_Perf3	6.89	0.77	0.69	0.91	

Table 6.26. Metrical Properties of Perc Mkt Perf Scale's Items

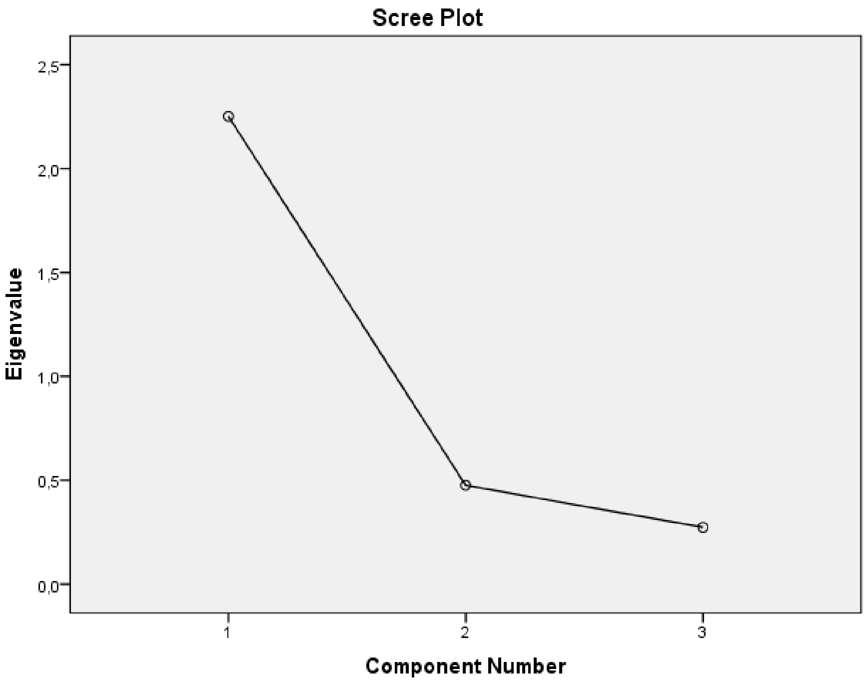


Figure 6.18 Perc Mkt Perf Scale's Scree Plot

Figure 6.18 shows the scree plot test of Perc Mkt Perf scale, that clearly indicated the 1 factor (i.e. monodimensional) solution as the best one.

6.6 Descriptive Statistics and Reliability Assessment of the Scales

The primary aim of this section is to report descriptive statistics and reliability values (i.e. Cronbach's Alpha) of the scales used in the survey instrument, as refined after the EFA.

In Table 6.27 are illustrated the descriptive statistics of the scales included in the model. All scales showed a close to normal distribution with skewness and kurtosis values included between ± 1 (except for the kurtosis of SAR scale which exhibited a slight deviation from normality), and optimal levels of internal consistency ranging from .78 to .97.

	N of Items	Mean	SD	Skewness	Kurtosis	Alpha
DFR	7	3.51	.86	-.61	.07	.93
DHR	5	3.36	.84	-.44	.08	.88
TMS	5	3.34	1.01	-.56	-.09	.96
AIT	4	3.10	.88	-.04	-.24	.89
SAR	4	3.41	.69	-.76	1.64	.79
IC	4	3.69	.86	-.69	.41	.89
CL	5	3.26	.89	-.29	-.22	.92
DM	8	3.33	.94	-.56	.06	.95
Dig_Inn_D&D_Hard	3	3.09	1.10	-.38	-.55	.78
Dig_Inn_D&D_Soft	3	3.36	1.10	-.46	-.70	.80
Dig_Inn_Man_Hard	5	2.63	1.07	.12	-1.00	.82
Dig_Inn_Man_Soft	5	3.38	1.01	-.49	-.37	.84
Dig_Inn_Prd	6	2.63	1.13	.27	-.98	.92
Per_Inn_Prf	12	2.98	.96	-.18	-.27	.96
Per_Fin_Prf	6	3.09	.83	-.54	.96	.97
Per_Mkt_Prf	3	3.42	.78	-.59	.67	.83

Table 6.27. Descriptive Statistics and Reliability of the Model's Scales

6.7 Model and Hypotheses Testing

Over the years, methods used to test mediation, ad more in general latent variable models, have grown in sophistication. For instance, the rise of structural equation modeling (SEM) in social sciences has been observed, which allows researchers to examine how well a conceptual model that links some focal variable X to some outcome Y through one or more intervening pathways fits the observed data (A. F. Hayes, 2009).

In order to test the hypotheses of the present study, a PLS-SEM approach was conducted including the scales described and analyzed above as manifest variables, and HODC, DMC and PERFORMANCE as latent constructs (see Figure 6.22). In particular, it was hypothesized that HODC (measured by the following indicators: DFR, DHR, TMS, AIT, SAR, IC, CL, DM) influences firms' performance level (measured by Dig_Inn_D&D Hard, Dig_Inn_D&D Soft, Dig_Inn_Man Hard, Dig_Inn-Man_Soft, Dig_Inn_Prod) both directly and through the mediation of DMC (measured by Perc_Inn_Perf, Perc_Fin_Perf, Perc_Mkt_Perf).

SEM procedures, implemented through PLS Graph, are used here to perform a simultaneous evaluation of both the quality of measurement (i.e. the measurement model) and construct interrelationships (i.e. the structural model) (Subramani, 2004). PLS Graph provides the ability to model latent constructs even under conditions of non-normality and small to medium-size samples (Chin et al., 2003). The rationale and theoretical explanations of the use of a PLS-SEM approach are described in detail in section 4.6.

As reported by Hair et al. (2014), PLS-SEM does not assume the data are normally distributed, which implies that parametric significance tests used in regression analyses cannot be applied to test whether coefficients such as outer weights, outer loadings, and path coefficients are significant. Instead, PLS-SEM relies on a nonparametric bootstrap procedure (Davison & Hinkley, 1997; Efron & Tibshirani, 1986) to test coefficients for their significance (Hair et al., 2014).

Both the measurement and path models were tested using partial least squares (PLS) structural equation modeling software, SmartPLS 3 (Ringle et al. , 2015). This software generates *t*-statistics for significance testing for all the estimated parameters, using bootstrap procedure. Through this process, a large number of subsamples (e.g., 1000) are taken from the original sample with replacement to give bootstrap standard errors, which in turn gives approximate *T*-values and the confidence intervals for significance testing of the structural paths. The Bootstrap result approximates the normality of data (Wong, 2013).

In the following sub-sections, both measurement and structural model are presented in depth and results of the testing procedure are discussed in detail.

6.7.1 Measurement model

Following the literature on this approach, for an initial assessment of PLS-SEM model some essential elements have been covered in this research report (Hair et al., 2011; Hair et al., 2014; Wong, 2013) Therefore, Psychometric properties of the reflective constructs were assessed by examining *internal consistency*, *convergent validity*, and *discriminant validity*. Through SmartPLS all factor loadings and t-statistics, cross-loadings, average variance extracted (AVE), Cronbach's alphas, and composite reliability scores have been calculated.

Internal consistency was evaluated by examining Cronbach's alpha and composite reliability score. Values higher than 0.70 for both Cronbach's alphas and composite reliability scores indicate that internal consistency is strong. Table 6.28 indicates Cronbach's alpha values which range from 0.82 to 0.93 for the latent variables, showing strong internal consistencies. Composite reliability (CR) scores for the same constructs range from 0.89 to 0.94, also indicating high internal consistencies.

Convergent and discriminant validities were assessed through confirmatory factor analysis (CFA) by examining factor structure, AVE, and interconstruct correlations.

For *convergent validity*, in a CFA of reflective constructs, outer loadings should be 0.70 or higher and AVE 0.50 or higher for every construct (Bagozzi & Yi, 1988; Hair et al., 2014). However, for an exploratory research, outer loadings values of 0.40 or higher are acceptable (Hulland, 1999).

As showed in Table 6.28, outer loadings range from 0.61 to 0.91. All loadings are highly significant ($p < 0.001$); AVE values range from 0.65 to 0.73.

Construct	Scale	Mean	SD	Loadings	t-Statistics	CR	Alpha	AVE
HODC	DFR	3.51	.86	0.91	59.65	0.94	0.93	0.68
	DHR	3.36	.84	0.82	20.01			
	TMS	3.34	1.01	0.86	33.10			
	AIT	3.10	.88	0.79	18.77			
	SAR	3.41	.69	0.61	7.31			
	IC	3.69	.86	0.84	27.09			
	CL	3.26	.89	0.85	27.18			
	DM	3.33	.94	0.89	31.94			
DMC	Dig_Inn_D&D_Hard	3.09	1.10	0.76	17.99	0.90	0.86	0.65
	Dig_Inn_D&D_Soft	3.36	1.10	0.83	26.37			
	Dig_Inn_Man_Hard	2.63	1.07	0.86	25.42			
	Dig_Inn_Man_Soft	3.38	1.01	0.84	25.93			
	Dig_Inn_Prd	2.63	1.13	0.73	13.23			
PERFORMANCE	Per_Inn_Prf	2.98	.96	0.87	38.70	0.89	0.82	0.73
	Per_Fin_Prf	3.09	.83	0.83	15.86			
	Per_Mkt_Prf	3.42	.78	0.87	28.90			

Table 6.28. Psychometric Properties of the Constructs

Concerning *discriminant validity*, in a CFA an item needs to load more highly on its own construct than on a different construct, and the "square root" of AVE of each latent variable should be greater than the correlations among the latent variables (Fornell & Larcker, 1981). As shown in Table 6.29, all the loadings for the inner model constructs are greater than all the cross-loadings. Some of these cross-loadings are relatively high (the highest shows a value of 0.70). This is common in published research when the indicators reflect correlated constructs (Agarwal & Karahanna, 2000; Karimi & Walter, 2015). Considering the accepted criterion that loadings must be greater than crossloadings, which is here addressed, these relatively high cross-loadings do not invalidate construct validity.

Scale	Construct		
	HODC	DMC	PERFORMANCE
DFR	**0.91**	0.68	0.66
DHR	**0.82**	0.58	0.51
TMS	**0.86**	0.54	0.58
AIT	**0.79**	0.62	0.53
SAR	**0.61**	0.37	0.51
IC	**0.84**	0.56	0.59
CL	**0.85**	0.58	0.59
DM	**0.89**	0.67	0.62
Dig_Inn_D&D_Hard	0.52	**0.76**	0.46
Dig_Inn_D&D_Soft	0.62	**0.83**	0.53
Dig_Inn_Man_Hard	0.55	**0.86**	0.63
Dig_Inn_Man_Soft	0.57	**0.84**	0.52
Dig_Inn_Prd	0.57	**0.73**	0.52
Per_Inn_Prf	0.70	0.65	**0.87**
Per_Fin_Prf	0.46	0.45	**0.83**
Per_Mkt_Prf	0.60	0.56	**0.87**

Table 6.29. Cross-loadings

In Table 6.30 diagonal values (in bold font) are square root of AVE, while off diagonal values are inter-constructs correlations. This table shows that the square root of AVE of each construct is greater than its correlations with other constructs.

	HODC	DMC	PERFORMANCE
HODC	**0,83**		
DMC	0,70	**0,81**	
PERFORMANCE	0,66	0,70	**0,86**

Table 6.30. Square Root of AVE and Constructs Correlations

Therefore, the results presented so far support both convergent and discriminant validities of the model constructs.

6.7.2 Structural Model

Having established the validity of the measures, the next step was to test the structural portion of the research model (Gefen, et al., 2000; Vinzi et al., 2010). The research model detailed conceptualized on Chapter 3 requires to conduct mediation analysis in order to indirectly assess the effect of the proposed predictor (HODC) on performance outcome (PERFORMANCE), through the proposed mediator (DMC). Hayes (2009) describes the model in figure 6.19 as the “simple mediation model”. In this model, **a** is the coefficient for X in a model predicting M from X, and **b** and **c’** are the coefficients in a model predicting Y from both M and X, respectively. In the language of path analysis, c' quantifies the direct effect of X, whereas the product of a and b quantifies the indirect effect of X on Y through M (A. F. Hayes, 2009).

In such a model, the *indirect effect* is interpreted as the amount by which two cases who differ by one unit on X are expected to differ on Y through X's effect on M, which in turn affects Y. A statistically and practically significant indirect effect is a necessary component of mediation (Preacher & Hayes, 2004).

The *direct effect* is interpreted as the part of the effect of X on Y that is independent of the pathway through M (A. F. Hayes, 2009).

When the effect of *X* on *Y* decreases to zero with the inclusion of *M*, *perfect mediation* is said to have occurred (James & Brett, 1984, call this situation *complete mediation*). When the effect of *X* on *Y* decreases by a nontrivial amount, but not to zero, *partial mediation* is said to have occurred (James & Brett, 1984; Preacher & Hayes, 2004).

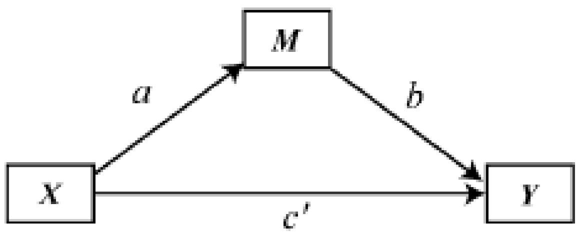


Figure 6. 19. Simple Mediation Model (Source: Hayes, 2009)

Preacher and Hayes (2004) argued that the utility of mediation analysis stems from its capacity to go beyond the merely descriptive to a more functional understanding of the relationships among variables. (Preacher & Hayes, 2004).

6.7.2.1 Results of the Basic Model

Primarily, we tested the relationship between HODC e Performance (H1) without including any other variable. This first basic model showed in Figure 6.20 does not consider DMC. However, it is essential to prior verify the robustness of the relationship between HODC and performance as a baseline to evaluate the increase in the prediction of performance after the inclusion of the mediating variable (DMC) and the control variables. As it is represented in the diagram below, the model is significant and shows a strong and positive effect of HODC on PERFORMANCE (ß = 0.701, t-value = 12.563, p-value < 0.001), fully supporting H1. Approximately 49% of the performance is explained by HODC (R^2 = 0.491).

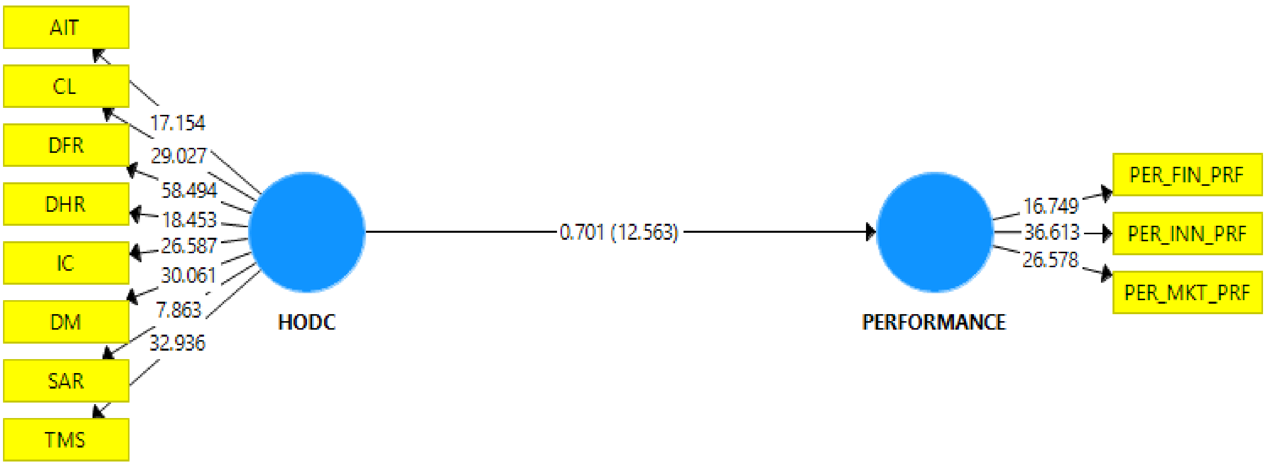


Figure 6.20. Basic Model of the Direct Effect of HODC on Performance not Including the Mediator

Subsequently, the mediation model was examined. As showed both in Table 6.30 and in diagrams 6.22 and 6.23, the effect of HODC on PERFORMANCE remained positive and significant even including the mediator (DMC) in the equation, with a large effect size. This result further supports H1. Similarly, HODC indicated a highly positive and significant effect on DMC, confirming Hypothesis 2 (H2). Furthermore, DMC exhibited a positive and significant effect on performance, suggesting that also Hypothesis 3 (H3) is fully supported. Noteworthy, by including DMC in the model the R square of Performance raised from 0.49 to 0.545, showing that not only the DMC mediated the effect of HODC on Performance, but also contributed to the prediction of Performance independently from HODC. All statistical t tests for model parameters showed p levels lower than 0.001. Furthermore, none of the confidence intervals of path coefficients estimated reported in Table 6.30 (both with normal and biased corrected procedures) included zero. Overall, these results indicate that all the hypothesized path relationship are statistically significant and robustly support H1, H2 and H3.

To test the mediation effect of DMC on PERFORMANCE (H4), Shrout and Bolger's tests were used, as presented in Table 6.30 (Shrout & Bolger, 2002). As recommended in Shrout and Bolger (2002), the confidence interval of the indirect effect was calculated empirically using bootstrapping samples.

Both normal and biased corrected confidence intervals (CI) were computed. The two CI are very similar in our data, indicating minimum skewing. In accordance with the procedure proposed by the above mentioned authors, it is possible to conclude that the effect of HODC on firms performance is partially mediated by DMC. This conclusion is based on the following steps: (1) HODC is positively related with PERFORMANCE since the total effect (C in Table 6.30) is significant; (2) the coefficient for the mediation path (Indirect effect, or "a × b" in Table 6.30) is significant; in addition, (3) when the mediation path is controlled for, the direct effect of HODC on firm performance (c' in Table 6.30) is reduced but remain significant. Therefore, since the effect of HODC on PERFORMANCE remained significant even including the mediator (DMC) in the equation, evidence is provided in favor of the partial mediation hypothesis (H4).

All statistical tests on the path coefficients are significant at <0.001 alpha value, and, in accordance with bootstrapping testing procedure, none of the path coefficients CI includes zero.

As regards the general goodness of the model fit, the basic mediation model (Fig. 6.22, 6.23) showed an adequate fit to the data as confirmed by the following indices: 1) Standardized Root Mean Square Residual (SRMR) = 0.077 (criteria for a good fit is SRMR <0.10, or <0.08 in a more conservative version); 2) A large portion of variance for both DMC (49%) and PERFORMANCE (54.5%) was explained by the predictors included. These results support the adjustment of the model to our data.

In order provide further evidence to exclude that the effect of HODC on firm performance is totally mediated by DMC, another model was analyzed by removing the direct effect between HODC and performance (see Figure 6.21) .

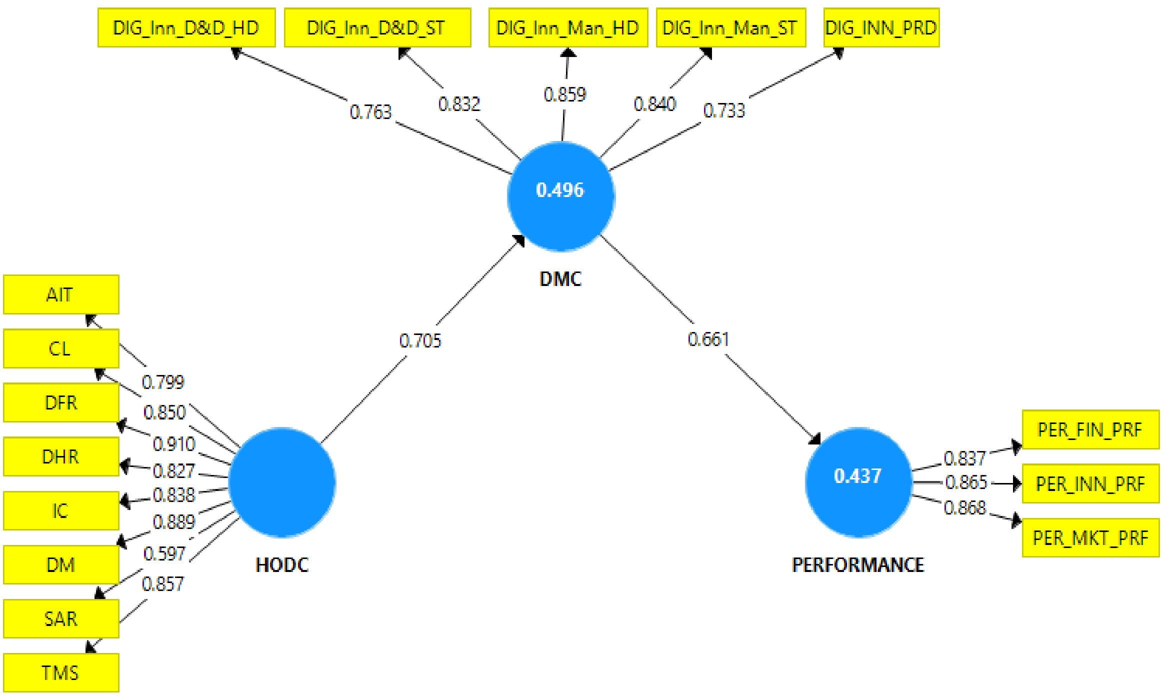


Figure 6.21. Complete Mediation Diagram

Results clearly showed a marked decrease in the fit indices: SRMR shows an increase from 0.077 to 0.100, reducing its goodness; R square of PERFORMANCE is considerably reduced from 0.545 to 0.437. These results confirm that the partial mediation model is the best solution and provide evidence that also H4 is fully supported.

Path	Effect	Est.	Mean	SE	t-statistic	Significance level (2-tailed)	95% CI	95% CI Bias Corrected
a	**HODC→DMC**	0.702	0.706	0.048	14.616	$p<0.001$	(0.596, 0.785)	(0.569, 0.777)
b	**DMC→PERF**	0.340	0.342	0.095	3.592	$p<0.001$	(0.160, 0.515)	(0.175, 0.525)
c'	**HODC→PERF**	0.459	0.459	0.102	4.447	$p<0.001$	(0.266, 0.647)	(0.245, 0.634)
A x b	**HODC→ DMC→PERF (indirect effect)**	0.239	0.235	0.069	3.436	$p<0.001$	(0.111, 0.369)	(0.117, 0.372)
C	**HODC→PERF**	0.697	0.697	0.061	11.505	$p<0.001$	(0.567, 0.810)	(0.569, 0.810)
	Effect size (R^2 of PERFORMANCE)	54.5%						

Table 6.30. Testing Direct and Indirect Model Paths

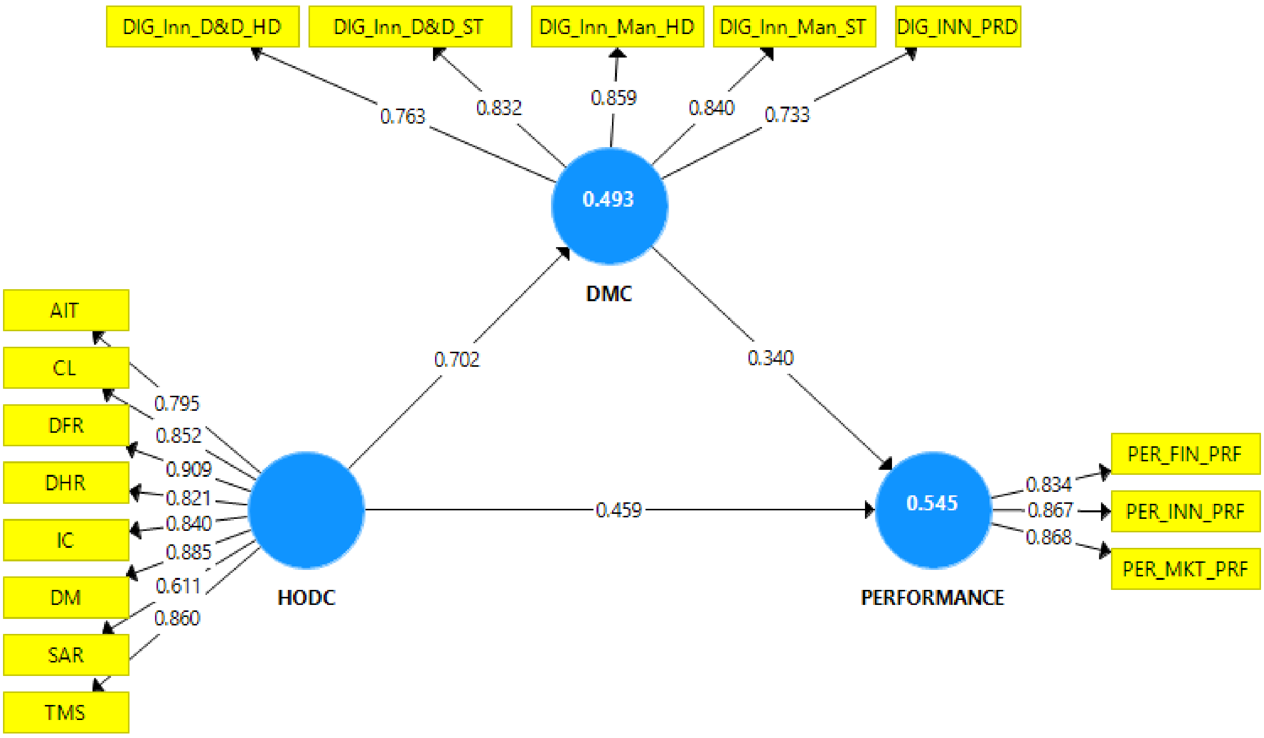


Figure 6.22. Mediation Model Diagram

Path Diagram of the basic mediation model: the diagram in figure 6.22 shows the constructs of the mediation model together with the relevant indicators. Following the traditional notation of the SEM approach, latent variables are represented by circles, whereas manifest variables through rectangular figures.

The numbers inside the latent variables - DMC and PERFORMANCE - stand for the R^2 values. Furthermore, values within the arrows represent path coefficients (i.e. for the structural/inner model, linking the latent variables included in the model) and outer of factor loadings for the measurement model (i.e. arrows directed from the constructs to the indicators). More schematically(Wong, 2013):

- **Numbers in the circles:** show how much the variance of the latent variable is being explained by the other latent variables.
- **Numbers on the arrows:** are called the *path coefficients*. They explain the strength of the effect of one variable on another variable. The weight of different path coefficients allow to rank their relative statistical importance.

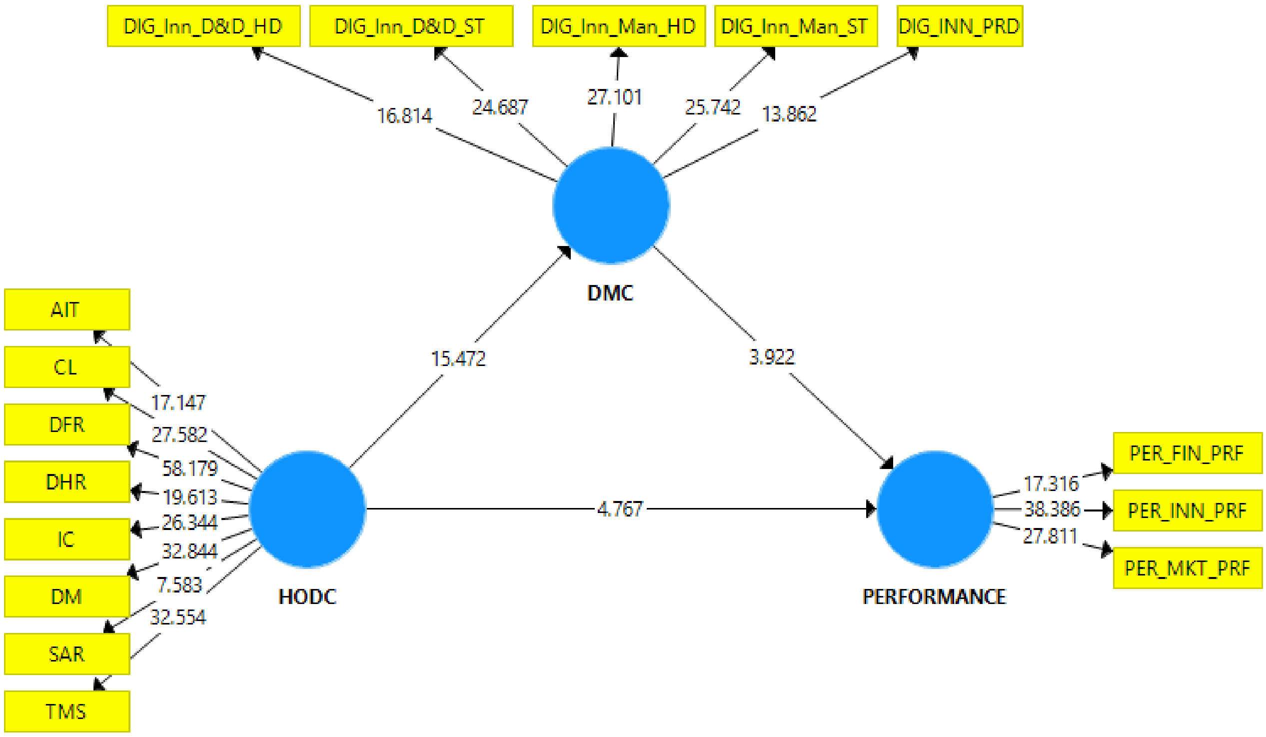


Figure 6.23. Mediation Model Diagram with Bootstrapping

Figure 6.23 shows the Path Diagram of the basic mediation model with bootstrapping estimation of t test values for all parameters: manifest variables are represented as rectangles, latent variables as circles, factor loadings as arrows directed from the constructs to the indicators (t test values for the factor loadings are reported on them), path coefficients as arrows linking latent variables included in the model (t test values for the direct path coefficients are reported on them).

Overall, all the hypotheses of the study were confirmed by the PLS model analyzed (see table 6.31). However, considering that no potential confounds were included in the base model, it is possible that the results would change considerably if some important control variables were included in the model. This further analysis is conducted in the section below that presents the refined model including control variables.

Hypotheses	Result
H1: Higher-order dynamic capabilities have a positive direct effect on firm performance.	Supported
H2: Higher order dynamic capabilities generate and positively influence digital manufacturing capabilities	Supported
H3: Digital manufacturing capabilities have a positive influence on performance	Supported
H4: The impact of higher-order dynamic capabilities on performance is partially mediated by the extent to which a firm develops digital manufacturing capabilities	Supported

Table 6.31. Summary of Hypothesis Testing

6.7.2.2 Refined Model with Control Variables

In order to test whether the mediation model is robust even when some of the control variables present in the research instrument are included, further analyses were performed by using PLS-SEM.

Many control variables inserted in the model were irrelevant (they produced non-significant results, obtaining non-significant path coefficients for p-value > 0.05, corresponding to t-values < 1.96). For this reason these control variables were excluded. Specifically they were: Firm Age, Product Size (i.e. type of production), and Turnover. These results indicate that, for the present model and sample involved, these firm characteristics do not affect significantly neither the development of DMC nor performance outputs.

In the diagram below (figure 6.24), the mediation model is represented including even those control variables that showed significant path coefficients/t-values. In more details, the variable *Use of digital technology* (i.e. "Use_Tech" in the diagram) positively affects DMC, showing high values of path coefficient (β = 0.493, t-value = 7.457) and indicating that firms which are currently using or strongly considering to use different digital technologies are more likely to have better digital manufacturing capabilities. Another variable that positively affects DMC is Expend_Dig_Inn (i.e. percentage of expenditures in digital innovation on the overall sales), even if with lower values of significance (β = 0.113, t-value = 1.938). This indicates that firms which invest higher percentage of their sales in digital innovation are able to develop stronger digital manufacturing capabilities.

Concerning the dependant variable (i.e. PERFORMANCE), two control variables have been included in the model: *Number of Employees* (see "N. Employees" in the diagram) showed a positive and significant effect on PERFORMANCE (β = 0.173, t-value = 2.623), indicating that the size of the firm positively influences firm performance. Furthermore, *Market Dynamism* (i.e. MKT_Dynamism in the diagram) – which represents the volatility and unpredictability of the firm's external environment (Miller & Friesen, 1983) – indicated a positive effect on PERFORMANCE (β = 0.138, t-value = 1.715), close to be significant (p-value= 0.087).

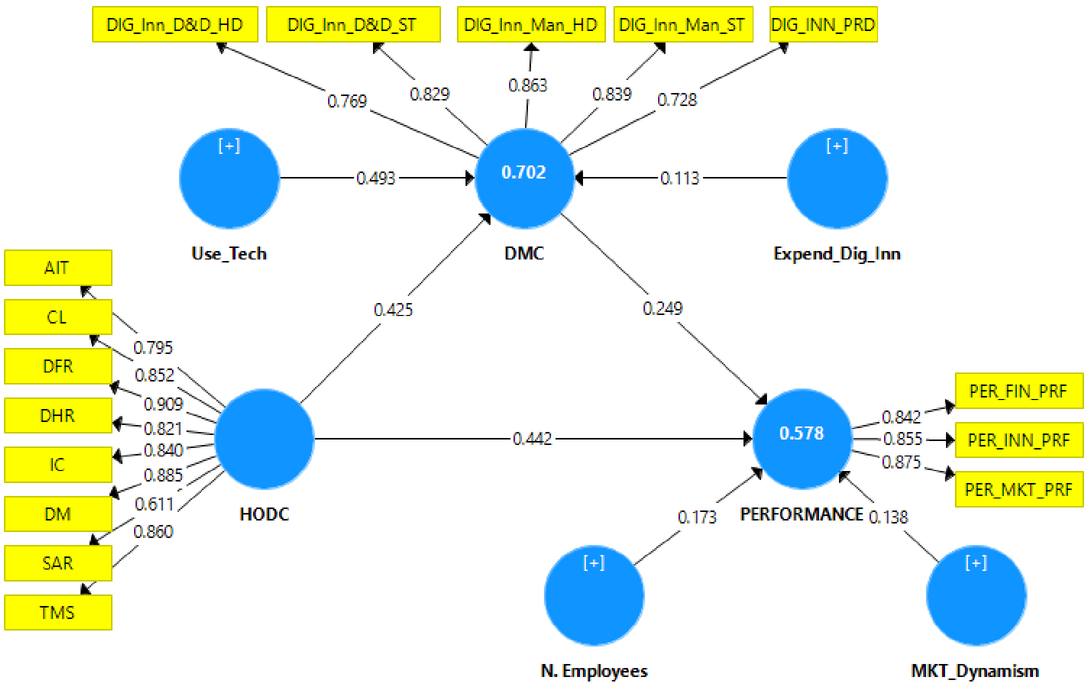


Figure 6.24 Mediation Model Diagram with control Variables

It is worth noting that Market Dynamism was found to have also a greatly positive and significant relationship with the predictor of the research model (HODC), showing a path coefficient of 0.446 (and t-value = 5.468, with a significance of p-value < 0.001). This last result supports the theoretical foundations of this study, according to which dynamic capabilities are implemented to respond to the "need to change" originated by the dynamism of the environment in which firms operate in order to obtain a sustainable competitive advantage over rivals (Drnevich & Kriauciunas, 2011; Helfat et al., 2007; Schilke, 2014; Winter, 2003; Zahra et al., 2006; Zollo & Winter, 2002). Hence, our result supports this part of the literature, highlighting a direct and positive link between these two dimensions (i.e. a positive influence of MKT_Dynamism on PERFORMANCE), in addition to the high-order dynamic capabilities-performance (i.e. competitive advantage) relationship. This path coefficient is reported in the path diagram represented in figure 6.25. As showed in the diagram, this connection does not alter the path coefficients of the basic mediation model neither in terms of significance nor in terms of the magnitude of the effects.

In conclusion, overall after the introduction of the above mentioned control variables, the path coefficients among the constructs of the basic mediation model (i.e. the structural inner model), while slightly decreasing in size, remained fully significant. Thus, the introduction of these control variables does not alter the mediating model assumptions, further supporting the hypothesized and tested partial mediation.

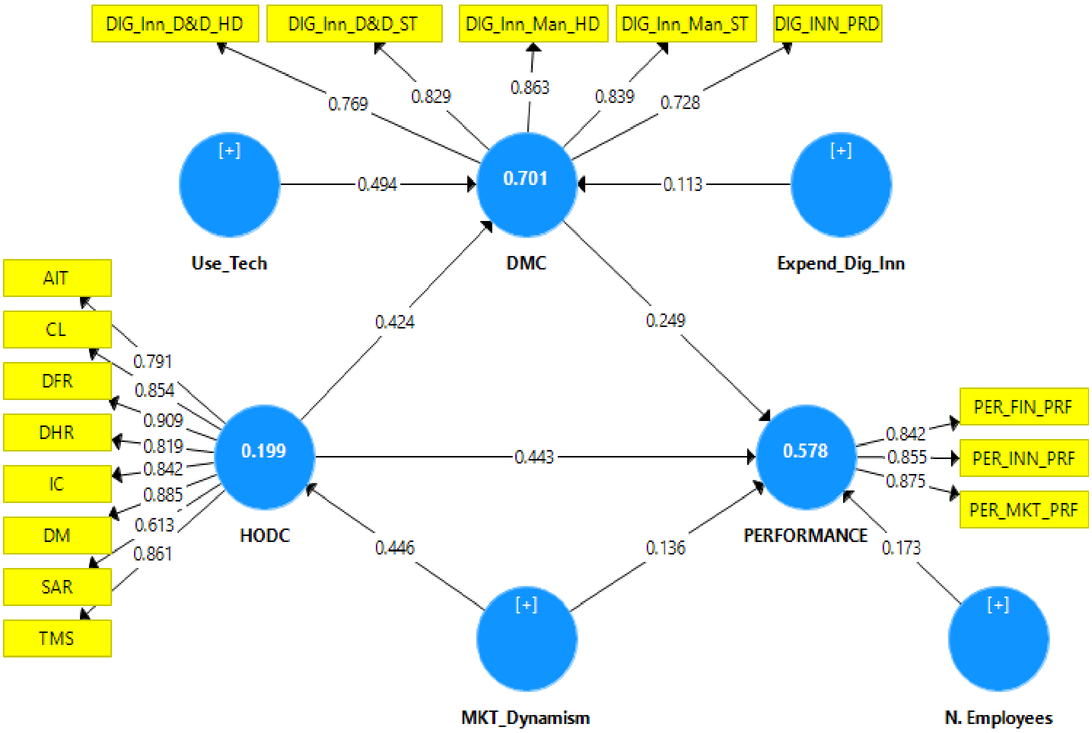


Figure 6.25. Mediation Model Diagram with control Variables

6.8 Chapter Summary

This chapter described the results of the web-based survey, and tested the conceptual research model and the associated hypotheses. After an explanation of the data collection procedures and a discussion about the adequacy of the sample, the data analysis and results were presented. This included the sample profile, EFA, and the testing of the measurement and structural research model together with its relevant hypotheses. Discussion of the findings, conclusions and limitations of the research are presented in the next chapter.

7. Chapter VII: Discussion and Conclusions

7.1 Introduction

The aim of this chapter is to discuss and draw conclusions from the results obtained in this research. To this end, empirical evidences are critically analyzed and discussed in accordance with the reference literature. Then, the research question and objectives of this study are addressed. Finally, this chapter presents an analysis of the contributions of the research as well as its limitations and suggestions for future research directions.

7.2 Discussions and Theoretical Implications

The purpose of this study was to develop and validate a model that explained the relationship among different orders of dynamic capabilities and superior firm performance. Therefore, the study presented a main research question and four hypotheses connected to the conceptual research model:

RQ: *What are the factors that drive the development of digital manufacturing capabilities (DMC) and to what extent does it affect organizational performance?*

Hence, in order to answer this question, three research objectives were set in Chapter 1:

RO1: Develop a clear understanding of the *Digital Manufacturing Capabilities* (DMC);

RO2: Explore what are the factors that drive the development of *Digital Manufacturing Capabilities*;

RO3: Understand and assess the extent to which dynamic and digital manufacturing capabilities affect organizational performance.

The first and second objectives were successfully accomplished by the extended literature review on Resource-Based View (RBV), Dynamic Capabilities View (DCV) and Disruptive Innovation theory presented in Chapter 2. The literature review allowed the identification of theoretical concepts that were fundamental for the development of the conceptual research model described in Chapter 3.

In order to achieve the third research objective, and answer the main research question, the conceptual model and its relevant hypotheses were tested through a PLS-SEM approach. Using a sample data from manufacturing companies' senior executives and managers, we found direct associations between higher-order dynamic capabilities (HODC) and firm performance (H1 supported), between higher-order dynamic capabilities and the development of digital manufacturing capabilities (H2 supported), and between digital manufacturing capabilities and firm performance (H3 supported). The test of the structural model also indicated that impact of higher-order dynamic capabilities on performance is partially mediated by the presence of digital manufacturing capabilities, supporting H4. Path coefficients from the structural model showed that the relatively majority of the effect of higher-order dynamic capabilities on performance is achieved directly. However, a strongly significant and positive effect of digital manufacturing capabilities on performance was registered. In this way the study was able to effectively and entirely address the main research question. In addition, even including in the model several control variables, it resulted robust and further supported the hypothesized partial mediation.

7.3 Theoretical and Managerial Contributions of the study

This study provides several key contributions, both theoretical and empirical. Firstly, through a systematic analysis and review of the literature it was possible to shed light on the state of the art of the existing research concerning the digital transformation of manufacturing, and provide solid theoretical foundations for investigating in depth this phenomenon of interest. Hence, by drawing upon Resource-Based View (RBV), Dynamic Capabilities View (DCV) and Disruptive Innovation theory, this research introduced a totally new construct in the literature: the *digital manufacturing capabilities*. DMC are lower-order dynamic capabilities, as they affect change in the firm resource base or firm ordinary capabilities (i.e. manufacturing capabilities) (Winter, 2003). Particularly, this study defined DMC as *the extent to which manufacturers use digital disruptive technological innovation to reconfigure their distinctive operational capabilities and resources (i.e. by enhancing the design/development, manufacturing and features of their products), in order to meet the competitive needs of the firm.* This new construct was operationalized in the research instrument, and its reliability and validity were assessed and confirmed through statistical analyses (see chapter 6). In this perspective, the development of the research instrument required a significant effort in order to operationalize RPV concepts based on disruptive innovation theory, create a new construct and include validated measures and control variables from the Management and IS literature. To do so, starting from some important empirical evidence achieved through qualitative multiple-case studies, both an inductive and deductive approach was used to conduct the review of the relevant academic literature as well as of the most updated specialized literature from the industry. The present work demonstrated that digital manufacturing capabilities not only have a positive effect on firm performance, improving its competitive advantage over rivals, but they also partially mediate the positive effect that higher-order dynamic capabilities have on performance.

The objective and investigation of this research resulted consistent with the suggestion of Shilke (2014) for future research directions. The author, in his recent study, argued that "*firms develop multiple types of dynamic capabilities (e.g., in the fields of alliances and new product development, but also in information* *technology, marketing, and mergers); thus, the effects of other capabilities, along with their potential complementarities, should also be investigated*" (O. Schilke, 2014).

More in general, results achieved by this research provide several contributions to the research fields of Strategic and Innovation Management as well as Information Systems, and their reference literature.

For instance, concerning the important topic of *process innovation* which refers to the introduction of new elements into an organization's operations (Schilke, 2014), this was measured here through the research instrument with several items (e.g. "*My organization allocates adequate funds for the research and development of innovative digital technologies (ICT) to support business process"; "My organization allocates adequate funds for the adoption of innovative digital technologies (ICT) to support business process"; "Our culture encourages the development of new, innovative processes"; We see our role as leveraging from innovative digital technologies to improve our business process"*). These items, included as reflective indicators of the higher-order dynamic capabilities construct, on average reported high scores in the descriptive statistics and resulted highly correlated as well as connected to the construct of DMC (which reflects the innovation of the manufacturing process through items such as "*My organization uses digital technologies such as Additive Manufacturing tools (e.g. 3D Printing, etc.) to improve manufacturing processes*", etc.). This evidence demonstrate that the majority of the executives who participated in this investigation perceive their organization as investing in the continuous innovation and improvement of processes.

Moreover, *firm size* can enhance competitive advantage by, for example, facilitating access to a lower cost of capital while simultaneously lowering risk (Chang & Thomas, 1989). Relying on the literature, firm size was here assessed based on a firm's total number of full-time employees. As discussed in chapter 6, a significant positive effect of this variable on firm performance was found, that confirms the theoretical foundations mentioned above. It is worth noting that, conversely, this dimension did not show to influence the firm's dynamic capabilities (i.e. neither HODC nor DMC), rejecting the assumption of some literature that larger firms may be able to dedicate more resources to developing their change routines (Schilke, 2014).

Another firm dimension introduced in the research model as a control variable was *Firm age*, measured in terms of the number of years since the establishment of the firm. Firm age has been suggested to influence a firm's competitive advantage (Zahra et al., 2000) as well as the extent of patterned forms of behavior that underpin dynamic capabilities (Helfat & Peteraf, 2003). However, by testing the conceptual model, no significant effect of firm age on the model constructs was found.

Recent influential literature on dynamic capabilities has particularly emphasized the role of environmental dynamism as a potentially important contextual variable (Helfat et al., 2007; Helfat & Winter, 2011; Zahra et al., 2006). Consequently, this study investigated the effect of *Market Dynamism* (operationalization of the construct is described in chapter 5) on the model constructs, and found out that it plays a key role in the link between dynamic capabilities and competitive advantage. This investigation contributes to answering the question "*under what conditions does the presence of DC in firms generate competitive advantage?: arguably one of the most interesting questions in the field of strategic management today*" (Verona & Zollo, 2011: 537). Evidence from the survey demonstrated that the manufacturing settings are perceived by firms as a highly dynamic context, which in turn creates a critical need to change in the organizations that operate in this market. In such a turbulent environment, it is essential to establish change routines through which new resources are devised and existing ones reconfigured. Indeed, the effect of such a dynamic environment was found to be both significant and positive on high-order dynamic capabilities as well as on firm performance. This explains what the contextual conditions are in which these dynamic capabilities are built and, in turn, drive the development of more specific dynamic capabilities (i.e. digital manufacturing capabilities) in order to gain competitive advantage in the market. These observed effects demonstrate that effective modes of organizational adaptation are at least partly determined by environmental forces (Hrebiniak & Joyce, 1985).

The confirmed positive effect of the *use of innovative digital technologies* on digital manufacturing capabilities provides evidence that firms that adopted or internally developed innovative digital technologies as first movers or early followers, built at the same time essential digital manufacturing capabilities in order to support this disruptive technological change. The mediating relationship within the model shows that these firms (together with those ones who are strongly considering to implement these technologies soon) are more likely to gain competitive advantage over latecomers. Similar considerations can be done, even relying on a weaker observed positive effect, about the relationship between the percentage of expenditure in digital innovation over the total sales (included in the refined model as "Expend_Dig_Inn") and digital manufacturing capabilities. Dynamic capabilities can be considered as "strategic options" that allow firms to reshape their existing resource base when the opportunity or need arises (Kogut & Zander, 1996; O. Schilke, 2014). However, building and using dynamic capabilities can be costly, and these high costs can typically arise from the activities and the technical means involved in innovating the core processes and resources of the firm. Therefore, higher expenditure in digital innovation was found to positively affect the expansion of firm DMC.

In addition, this research empirically confirmed through a PLS-SEM approach the strong and positive direct relationship between higher-order dynamic capabilities (HODC) and firm performance (i.e. competitive advantage), as well as the partial mediation of DMC on this relationship.

This study contributes to research on dynamic capabilities also in another important ways. In fact, the construct of Higher-order dynamic capabilities was characterized in terms of systematically adapting the change in firm resources, processes and values (i.e. RPV framework) to the environmental dynamism. These capabilities create value and influence performances both directly and indirectly, by enhancing lower order dynamic capabilities - here represented by digital manufacturing capabilities – as well as positively impacting directly on firm performance (Daniel et al., 2014). Thus, the effect of higher-order dynamic capabilities on performance resulted partially mediated by digital manufacturing capabilities (i.e. lower order D.C.). These results are consistent with the recent study of Fainshmidt et al. (2016) and follow their suggestion to further investigate the relationships mentioned above: "*we find that the effect of higher-order dynamic capabilities on performance is partially mediated by lower-order dynamic capabilities. Thus, more studies looking into potential mediating mechanisms in the dynamic capabilities-performance relationship are needed*" (Fainshmidt et al., 2016). More in detail, the authors in their meta-analysis specified two path models: 1) one in which higher-order dynamic capabilities (i.e. the independent variable of the model) influence performance (i.e. the dependant variable) only indirectly through lower-order dynamic capabilities - configuring a complete mediation); 2) and another one in which higher-order dynamic capabilities affected both lower-order dynamic capabilities and organizational performance, while lower-order dynamic capabilities affected only organizational performance. The study found that the first model did not fit the data, being rejected, while the second model was statistically supported confirming that lower-order dynamic capabilities are affected by higher-order dynamic capabilities, but only partially mediate their effect on organizational performance. Their results showed that the effect of higher-order dynamic capabilities on performance is much higher (ß = 0.49) than the impact of lower-order when both are allowed direct paths to performance (represented by a modest path coefficient value of ß = 0.06) (Fainshmidt et al., 2016). Our model indicated the same relationship (with HODC having a relatively higher effect on performance than DMC), but with a much higher impact of DMC on performance (path coefficient value of ß = 0.34) if compared to their result.

By adapting the RPV framework to the topic and context under investigation, this study enriches also the Disruptive Innovation Theory of new important insights. Key constituents of RPV were identified, operationalized and measured as the constituents of higher-order dynamic capabilities that are systematically reshaped, extended and adapted to the contextual change. As above mentioned, the research demonstrated that, in the environment under investigation, they positively affect the creation of digital manufacturing capabilities in response to digital disruption. Karimi and Walter (2015), in their empirical work, examined the role of first-order dynamic capabilities (created by changing and adapting RPV) in the context of the newspaper industry (Karimi & Walter, 2015). Their model is somehow similar to the present conceptual model (i.e. represents a partial mediation effect), but the context investigated as well the instrument used are dissimilar. Differently from the authors, which adopted the RPV framework to characterize first-order dynamic capabilities as a second-order formative construct, in the present study RPV resulted as indicators measuring the reflective construct of higher-order dynamic capabilities. This difference can be explained in detail by the following statistical motivation: (1) very high correlations were found to exist among all the scales of the independent variable (i.e. HODC), that represent the operationalization of RPV; (2) the Principal Component Analysis (PCA) suggests the monodimensional solution (i.e. one-factor solution) as the best one, demonstrating that a clear distinction between resources, processes and values (i.e. R, P and V taken as separated dimensions as in Karimi and Walter, 2015) did not find any evidence within our sample and using the research instrument we developed and validated; (3) in addition, the Cronbach's Alpha calculated including all the scales of HODC showed a very high value (α =0.97), confirming the monodimensional solution. These evidences indicate that the scales which characterize the HODC construct in the instrument can be considered as reflective indicators of this construct, as well as the dimensions of the RPV framework have been shown to be homogeneous within HODC. For these reasons, in this study high-order dynamic capabilities resulted in a first-order reflective construct characterized by indicators reflecting RPV concepts. Thus, by complementing the dynamic capability view with the disruptive innovation theory (i.e. concepts from the RPV theoretical framework) in a specific fast changing context (i.e. the different industries included in the wide manufacturing sector) this study provides an original and considerable contribution to both the strategic management and IS literature. To the best of our knowledge, it is the first empirical study that includes and assess all this elements together in the context of manufacturing sector.

Finally, this work provides some *managerial implications* for manufacturing firms to respond to digital disruption. The abovementioned results suggest that they are able to do so by changing, adapting or extending their existing RPV on a systematic base, through the creation of established "change routines" (Collis, 1994; Levinthal & Rerup, 2006). Indeed, depending on the degree of dynamism of the context in which they operate, firms must evaluate the convenience of investing in building costly dynamic capabilities (in our case digital manufacturing capabilities, represented by the development or adoption of a set of disruptive digital innovations and skills) in order to obtain superior performance (i.e. competitive advantage). Acknowledging that building dynamic capabilities involves serious costs has implications for their potential value. If a firm rarely has a need to change, its performance relative to competitors may suffer when it devotes significant resources to developing these capabilities (Schilke, 2014). Consistent with the previous observation, it is essential to emphasize the importance of balancing the costs of a given dynamic capability and its actual use, assessing it as a strategic option for the firm. The positive effect of dynamic capabilities on a firm's competitive advantage will be comparatively higher when environmental dynamism is high (such as in the manufacturing sector). In these situations, rather than investing in the status quo, resources need to be appropriately allocated for building and using unique dynamic capabilities in order to innovate processes and create new products as well as to implement the actual efficiency, efficacy and financial and market performance (these dimensions were comprehended in the dependent variable of the model and registered high scores on average). The deployment of a structured *digital strategy* profoundly influences business goals and investments. As the present results demonstrated, it is not the technology itself that represents a company's "secret formula", but the carefully developed processes wrapped around it and the talent employed to operate it. These unique resources and processes can be very hard for rival firms to imitate, becoming an essential source of competitive advantage. That also provides a factor contributing to where production activities should be located: wherever people with the required skills can be recruited (Franklin, 2017).

In addition to resources and processes, even values (which in our operationalization included Innovative Culture, Common Language and Digital Mindset) need to change over time, since they ultimately determine what processes are in place through the overall strategy of the organization.

7.4 Conclusion, Limitations and Future Research Directions

The phenomenon of the digital transformation of the manufacturing sector is finding a growing interest at both practitioner and academic levels, but it is still in its infancy and needs deeper investigation. Digital technologies, innovations, and transformation, are fundamentally reshaping business processes, products, services, and relationships (Berman & Bell, 2011; Bharadwaj et al., 2013; Kallinikos, et al., 2013; Karimi & Walter, 2015; Yoo et al., 2010). Reference literature, in the fields of innovation and strategic management as well as IS, showed a gap concerning the emphasis on technology and organizational/cultural factors embedded in the RPV framework which may be systematically changed, extended or adapted to build specific dynamic capabilities essential to take advantage of the enabling role of technology in responding to disruptive innovation. Relying on a systematic literature analysis and review, this study provided several interesting insights covering the topic of interest by adopting the theoretical lenses of dynamic capabilities view and disruptive Innovation theory, integrated with the literature on digitization and digital transformation. Thus, the complex patterns of dynamic interdependencies among environmental turbulence, dynamic capabilities, advanced IT systems for manufacturing and superior firm performance were deeply investigated. It was empirically assessed and confirmed the role of firm higher-order dynamic capabilities in responding to the contextual dynamism - characterized by digital disruption - and positively affecting firm performance, through the partial mediation of digital manufacturing capabilities.

However, similar to any other empirical research, this work contains methodological strengths as well as some limitations. In particular, while we followed established guidelines in structuring our sample and its size is adequate for the PLS-SEM analysis (N=110), it is nevertheless not exhaustive and could reduce the statistical power in the test of some model parameters (for this reason for instance, some contextual variables could result to be not significant due to an high level of standard error). Moreover, for the same reason, it was not possible to conduct an EFA on all the items together (respecting the "rule of thumb" concerning the ratio between number of observations and number of items; MacCallum et al., 1999) to evaluate the discriminant validity of the instrument items. The EFA, as described in chapter 6, was conducted on each scale separately.

Another limitation is the cross-sectional nature of this study, which only allowed to capture the picture of the manufacturing companies' dynamic capabilities (including both HODC and DMC) and contextual change at a certain time. Although the literature shows a long tradition of empirical tests of mediation based on cross-sectional data and involving methods described by Baron and Kenny (1986) (e.g., Kenny et al., 1998; MacKinnon et al., 2002; Shadish et al., 2002; Shrout & Bolger, 2002), recent studies argued that cross-sectional examination of mediation may generate biased estimates of longitudinal mediation parameters (Baron & Kenny, 1986; Maxwell & Cole, 2007). By considering the findings of Maxwell and Cole (2007) concerning mediation in Psychological literature, future research should extend the results obtained here by carrying out longitudinal studies based on mediation models in order to better investigate causal processes that unfold over time. This would allow researchers to definitely prove the causal direction and to better assess the magnitude of the estimated parameters.

Furthermore, concerning the construct of performance (which here includes the scales of perceived innovation performance concerning the last three years of activity, perc. financial performance and perc. market performance), it was measured based on the perceptions of the respondents. A suitable follow-up of this research could be to collect objective measures for the dependent variable from the same or similar representative firms that had participated in the online survey. Thus, to corroborate the performance information obtained from manufacturing firms' top-managers, accounting performance data (e.g. ROI, ROE, etc.) should be collected for at least a subset of companies for which such information is available. Using public financial databases, company reports available on the firms' websites, or relying on information on organizational growth, it is possible to triangulate the dependent variable. Subsequently, it would be necessary to compare these archival data with perceptual responses and observe if both measures are significantly correlated.

Moreover, beyond the manufacturing sector, digital transformation can boost various industries by enhancing, extending, and redefining their physical or traditional products and services through digital content, reshaping the value propositions delivered or co-created with their customers, and originating new revenue streams to ensure their survival (Berman & Bell, 2011; Picard, 2000). For instance, the music industry was one of the first to experience the impact of digital revolution brought about by the forces of mobile innovation, social media, digitization, and the resulting changes in customer expectations. As discussed within this study, these same forces are disrupting the manufacturing sector and pushing it toward digitizing its core processes, creating more digital content, higher degree of product and service digitization (e.g. smart products), and deeper digital transformation. Further studies should investigate and compare the patterns resulting from this research in different sectors as well as regions of the world.

In conclusion, this study relies on the intention to take stock of existing research and expand the literature on digital transformation by drawing on strong theoretical foundations (i.e. DCV, RBV, RPV, etc.). In doing so, it will hopefully propel more focused theory building and discussion about this interesting topic starting from the implications resultant from the analyses carried out herein.

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