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Making digitalization effective: an exploration of the complementarity between digital technologies and organizational practices in the Italian Automotive Component Industry

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Summary

Despite substantial investments in **digital technologies**, often driven by forward-looking national policies, manufacturing firms are still far from making digitalization effective with limited evidence of increased **cost performance** shifting away from the growth visions of "Smart Manufacturing" and "Industry 4.0". Early information system literature suggests that to make a return on technological investment companies must changes **organizational practices** e.g., in resources, activities, capabilities, and collaborations while adopting digital technologies. However, current digital technologies have new technological features including computing, connectivity, data storage and processing capacities requiring new organizational practices. The objective of this thesis is to understand what are the properties of digital technologies and how these *enable* and *require* changes to decision-making and governance practices to increase the cost performance of manufacturing firms.

Using the **automotive industry** as the setting of the research, this thesis uses mixed-method research employing both quantitative data from 102 questionnaires and qualitative data from 10 case studies collected from a representative sample of Italian automotive suppliers. Adopting a phenomenon-based research approach this thesis started with a literature review on the main properties of two main forms of digital technologies that shape the digitalization phenomena: physical-digital interface technologies and network technologies. To investigate the complementarity between practices and digital technologies some logistic regressions have been performed keeping fixed the adoption of digital technologies and cost performance (the dependent variable). Having found some "surprising facts" this thesis uses an abductive approach and use a set of management theories to explain the results.

Concerning the physical-digital interface technologies and network technologies, this thesis found respectively the properties of **virtualization** and

traceability of physical devices in the shop floor, and **accessibility** and **synchronization** of a wide range of data throughout the organizations in a bi-directional communication framework between information systems and physical devices.

Concerning **decision-making**, the properties of these two forms of digital technologies make events, upon which decisions are made, respectively more analyzable and less equivocal making a data-driven decision-making approach diffused in the organization a compelling necessity to have an increased cost performance. It is urgent more than ever that the managers encourage a shift from an intuition-driven (experiential, unconscious, and holistic) to a data-driven decision-making approach (analytical, conscious, and sequential) through some practices that are discussed in this thesis.

To make digitalization effective inside the factory, this thesis found that - at an increasing rate of technology complexity, customization levels, and novelty of the two different forms of digital technologies – manufacturing firms should rely on **relational governance practices** based on co-creation and continuous collaboration with technology partners like **system integrators** that would allow the reduction of transaction costs and the sharing of technological and domain knowledge.

Concerning **governance practices** with **customers**, this thesis found that the traceability and virtualization properties of physical-digital interface technologies enhance the relational governance based on quasi-integration and trust. Second, the accessibility and synchronization of network technologies require long-term contractual governance because these technologies expose a supplier to opportunistic behaviors caused by behavioral uncertainty of customers. Taken together, the different forms of digital technologies and governance practices reduce the transaction costs among the partners and therefore increase incentives for suppliers to engage in process innovation activities aimed at reducing production costs.

This thesis found some **national approaches to digitalization** by comparing Italy and the US automotive components industry reflecting institutional differences between the two countries. Using a comparable sample, this thesis found that Italian auto plants, while adopting less physical-digital interface technologies concerning the US due to smaller firms' size, show a higher diffusion of network technologies and a data-driven decision-making approach. Due to the higher empowerment of workers in continuous improvement, the Italian approach to digitalization seems more a human-centered approach with a focus on data analysis and data integration. By contrast, the US approach to digitalization is more on the use of technology to face a critical skill gap.

Overall, these results point out how complex is for automotive suppliers to introduce process innovations and to enhance cost performance in the digital transformation context. On one hand, to improve cost performance, they have to invest in different and highly specific sets of digital technologies and, on the other hand, to change decision-making approaches, to manage their interplay with the governance mechanisms with technological partners and customers.

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Chapter 1

Introduction

1.1 Background

The automotive industry – one of the largest and most dynamic manufacturing supply chains – is facing a great complexity due to new product and process requirements, that are subject to high levels of international standards on safety and quality, sustainability, and efficiency. The digital transformation of manufacturing can mitigate not only the complexity but also the volatility, uncertainty, and ambiguity currently faced by the increasingly competitive and digitalized automotive sector. The challenges of the COVID-19 pandemic have dramatically imposed further actions by managers increasing their awareness of the need to accelerate the digitalization and digital transformation[1] to govern and not being overwhelmed by current change processes (Hanelt, Bohnsack, Marz, & Antunes Marante, 2020).

Yet, some key questions remain for managers. How should established manufacturing firms adopt digitalization? How they can create value from digitalization? Rather than trying to focus on the adoption of digital technologies only, managers need to focus on developing new organizational practices including governance practices, decision-making approaches, resources, activities, capabilities, and strategies that will allow the creation of value from digitalization (Björkdahl, 2020). In this thesis, **digitalization** refers to the increased generation and analysis of data through the adoption of digital technologies (e.g. sensors, RFID, machine vision, human-machine interfaces, software, digital platform) in the firm's product and inbound and outbound activities to increase internal efficiency and/or customer offerings (Björkdahl, 2020)

Investments in digitalization allow not only to "do new things", but also to "do things better" through increased operational efficiency, cost reduction, and business process improvement. The thesis focus on the last outcomes. A recent worldwide survey of 1,155 executives expects an average of 12.3% of cost reduction over five years (PwC, 2018). Indeed, digitalization can bring significant process improvements in manufacturing by reducing defects and reworks, minimizing

[1] The terms digitalization and digital transformation are used interchangeably in this thesis.

equipment breakdown and minor stoppages, increasing inventory control, supply chain transparency, safety, sustainability and ultimately reducing production cost (D. R. Sjödin, Parida, Leksell, & Petrovic, 2018).

In the innovation management literature, operational efficiency is considered as the outcome of process innovations (Davenport, 1993; Trantopoulos, von Krogh, Wallin, & Woerter, 2017). **Process innovation** is "the implementation of a new or significantly improved production or delivery methods. This includes significant changes in techniques, equipment and/or software" (OECD 2005, p. 9).

Implementing process innovations with digitalization (hereafter *digital process innovation*) is often highly problematic because it entails tacit knowledge, complex problem solving, learning by trial and error, and systemic changes into several components of a production system (Sjödin et al., 2018; Trantoupolos et al. 2017). The implementation of digital process innovations may lead to unanticipated technological challenges, new skills for the operating personnel, and significant change in the work practices (Trantoupolos et al. 2017). These complexities make digital process innovation a highly challenging and risky effort that extends well beyond the introduction of digital technologies (Sjödin et al., 2018).

Attracted by an encompassing policy-driven innovation discourse under the label of Industry 4.0 (Reischauer, 2018), several manufacturing firms are investing in digital technologies. In Italy, this discourse initiated by the Minister of Economic Development at the end of 2016 which put forward a national plan "Industria 4.0" (hereafter Industry 4.0 National Plan) whose main measure was to stimulate the investment in the digitalization of manufacturing in the form of depreciation allowance but also into competence development and technological infrastructure (MEF, MISE, MIUR, & ML, 2018)

As far as investment in digital technologies is economically feasible, thanks to these incentives, the key issue is not on the adoption of digital technologies *per se*, but how to purposefully use such technologies to increase the efficiency and therefore the competitiveness of the company. In other words, the key issue is how companies can generate value from digital technologies (Björkdahl, 2020; Martínez-Caro, Cegarra-Navarro, & Alfonso-Ruiz, 2020). Forward-looking managers should not think only economically on how to substitute old equipment or exploiting the financial advantages of national plans but on how such technologies once implemented will support innovation within the company (Trantoupolos et al., 2017). This forward-looking thinking offers far greater process innovation possibilities and greater cost reductions in the long term.

The literature has already shown that most manufacturing firms are better at sensing technological opportunities but less in seizing and shaping such technological opportunities and transforming organizations (North, Aramburu, & Lorenzo, 2019). Digitalization is a great challenge for manufacturing firms. Late adopters risk risks to be driven out to the market by advanced competitors in the same industry (Müller, Buliga, & Voigt, 2018) or the value being captured from firms outside the industry offering data analytics services (Susan Helper, Martins, & Seamans, 2019). Despite operational efficiency is a primary driver of digitalization investments, there is limited empirical evidence on the relationship between the adoption of digital technology and cost performance (Lorenz, Benninghaus, Friedli, & Netland, 2020; Guilherme Luz Tortorella & Fettermann, 2017).

We know from thirty years of academic research on information and digital technologies that without organizational and managerial changes cost performance improvement is limited if not null (for a recent review see e.g. Martínez-Caro et al., 2020). Yet, an investigation of the much-needed practices in the digitalization era is lacking from the empirical investigation. In this thesis, practice is referred to in the broadest sense of the word (encompassing e.g. decision-making approaches, governance practices, resources, activities, and capabilities).

1.2 Research Questions

As far as organizational practices are concerned, early research on enterprise information systems and the business value of information technology points to the need for changes in decision-making approaches toward data analysis and quantitative assessment (E Brynjolfsson, Hitt, & Kim, 2011), vertical collaboration (co-development and co-creation with partners at different levels of the value chain e.g. technology vendors, system integrators) and horizontal collaboration or governance (with partners at the same level of the value chain e.g. customers, suppliers) to have a business value from the investment in information technology (Melville et al., 2004). However, current studies do not consider the properties of a new generation of information technologies driving by recent technological advancements (e.g. in the fields of sensors, data storage and processing, connectivity protocols, and standardization) (Hanelt et al., 2020; Youngjin Yoo, Boland Jr, Lyytinen, & Majchrzak, 2012).

The main objective of this thesis is to *explore how digital technologies enable and require changes to decision-making approaches and governance practices to increase the cost performance of manufacturing firms*. This thesis analyses the impact of digitalization on organization at different levels: internally to the firm, concerning decision-making, and externally concerning horizontal and vertical governance practices. Such a multi-level approach is needed given the pervasiveness of digitalization that has the potential to transform not only the structure of the whole organization but also its relationship with external partners in the ecosystem (Nambisan, Wright, & Feldman, 2019).

The Nobel prize Herbert Simon argued that management is essentially organizational decision-making (Herbert A Simon, 1960): all organizational actions are initiated by decisions, and all decisions are commitment to actions. Therefore, a key to understand how data generated by digital technologies create value is to study how it drives decision-making (Bokrantz, Skoogh, Berlin, Wuest, & Stahre, 2020). Two main approaches can be found in manufacturing firms: the intuition-driven decision making (experiential, unconscious, and holistic) and the data-driven decision making (analytical, conscious, and sequential) (Flores-Garcia, Bruch, Wiktorsson, & Jackson, 2019). Some scholars argue that decision-making should be largely based on data analysis which could lead to better outcomes (e.g. E Brynjolfsson et al., 2011; Provost & Fawcett, 2013). Others suggest a more balanced approach where judgment and experience should be considered as well (e.g. Shah, Horne, & Capellá, 2012). In the management practice, confusion arises on which is the optimal decision-making approach when adopting digital technologies to achieve efficiency improvements. This thesis compares these two approaches, focusing on a particular subset of decision-making related to cost reduction, i.e. those "production decisions" taken at an operational level (Bloom, Garicano, Sadun, & Van Reenen, 2014). The first objective of this thesis is therefore to analyze the different approaches toward decision-making while adopting digital technologies and how these are linked to cost performance. The first research question of this thesis is the following:

RQ1. *What decision-making approach (intuition-driven vs data-driven) is the most beneficial to increase cost performance as manufacturing firms adopt digital technologies?*

Research has shown that the governance of inter-organizational relationships has a positive effect on the performances of supply chains (Dyer, 1996; Roehrich, Selviaridis, Kalra, Van der Valk, & Fang, 2020). Nowadays, the emergence of new ICT-based technologies, which drive digitalization, is varying the density of interactions between buyers and suppliers (Brun, Gereffi, & Zhan, 2019). Partners in the dyadic supply chain relationship should be aware of the implications that digitalization has on the governance of the relationships to manage transaction costs. An important source of transaction costs is *behavioral uncertainty* which refers to the ambiguities in understanding a partner's behavior due to the possibility of "strategic non-disclosure, disguise, or distortion of information" by the exchange partners (Williamson, 1985). Scholars argue that to manage behavioral uncertainty in inter-organizational relationships buyers and suppliers have two main governance practices: contractual and relational (G. Cao, Duan, & Li, 2015). Contractual governance manages the inter-organizational relationship by formal and explicit agreements that specify obligations and roles of exchange partners (e.g. concerning quality, price, delivery, reliability). By contrast, relational governance is based on relational norms such as trust, information sharing, partner flexibility, and joint problem-solving. Both supply chain governance mechanisms have been proved to have a positive effect on cost performance (Blome, Schoenherr, & Kaesser, 2013). It is widely acknowledged that information technologies support information and process integration in supply chain relationships. Thus, it is not a surprise the emergence of new digital technologies has spurred interest in supply chain research (e.g. Fatorachian & Kazemi, 2020). Current research has mainly focused on the effect of enterprise information systems (Jean, Kim, Lien, & Ro, 2020) and the perspective of customers (e.g. Blome et al., 2013).

However, digital technologies pose new challenges and opportunities for supply chain governance. A recent survey involving more than 1000 firms in the US and Europe found that only 8 % give a customer access to production information (Fetterman, 2019). Indeed, the collection and analysis of real-time data from digital technologies pose a new opportunity for control of customers that could use opportunistically such data how the suppliers use the production resources and possibly opt for a more efficient supplier. At the same time, digital technologies promise to increase the integration between customers and suppliers enhancing trust-based relationships. The second objective of this thesis is to provide a detailed understanding of how digitalization enables and requires changes to governance practices concerning relational and contractual governance. The third research question is the following:

RQ2. What governance practices (relational vs contractual) in the supply chain relationship are the most beneficial to increase cost performance as manufacturing firms adopt digital technologies?

To make digitalization effective, most manufacturing firms rely on external knowledge and technology sources and in particular on system integrators thanks to their ability to ability to combine and integrate different technologies based on hardware and software technological elements and to provide plant data and network connectivity (Kahle, Marcon, Ghezzi, & Frank, 2020). In this vein, innovation scholars found that modern-day manufacturing firms tend to rely on few and selected knowledge sources when focusing on process innovation because that it facilitates the exchange of tacit knowledge and its recombination with technological knowledge (Lorenz et al., 2020; Terjesen & Patel, 2017; Trantopoulos et al., 2017). However, it remains unclear when collaboration with external knowledge sources is beneficial to increase cost performance vis-à-vis the adoption of digital technologies (Lorenz et al., 2020).

The implementation of digital technologies (i.e. digital process innovation) entails a significant degree of uncertainty among the various partners, due to highly specialized knowledge that needs to be integrated (Kostis & Ritala, 2020). Reducing such uncertainty is critical for ensuring the successful execution of industrial B2B projects. This type of uncertainty is defined as *interpretative uncertainty* (Weber & Mayer, 2014), which refers to the misalignment of views on the process and the outcome due to the competence and domain-expertise difference among the firms involved (Kostis and Ritala, 2020). Weber and Mayer (2014) proposed that this type of uncertainty derives not from the transaction characteristics but different relational characteristics (i.e. the attributes of the parties relative to one another) such as industry and technology membership. In this thesis, an additional source of uncertainty is introduced that has not yet been analyzed in the context of industrial relationships: technology characteristics. To manage and reduce interpretative uncertainty resulting from the implementation of digital technologies firms should configure proper governance practices that reduce such interpretative uncertainty. The literature argues that governance practices between a customer and technological partner should move from transactional to relational as the relationship unfolds (Sjödin, 2019) relying on co-creating logic and long-term commitment

However, there is no empirical evidence if and when these governance practices between system integrators and manufacturers lead to cost performance improvements for manufacturers. Current research discusses the evolution of governance practices mainly using a time-based perspective (Kamalaldin, Linde, Sjödin, & Parida, 2020). However, it remains unclear what triggers the change of governance practices from transactional to relational apart from time. Recently, Sjödin (2019) proposes to focus on the technological characteristics in terms of complexity, novelty, and customization when selecting appropriate governance practices in joint process innovation projects. To fill this gap, the third research question of this thesis is the following:

RQ3. *What governance practices (transactional vs relational) with system integrators are the most beneficial to increase cost performance as manufacturing firms adopt digital technologies?*

Finally, this thesis provides some preliminary analysis of the impact of institutional conditions of countries on digitalization approaches by firms (Hanelt et al., 2020). The extent to which digitalization happens is a result of different elements including the types of management practices and digital technologies adopted but also the industry environment (Mithas, Tafti, & Mitchell, 2013) and country-level policies (MacDougall, 2014). The *legal and infrastructural conditions* of a country can exhort a great impact on the way digitalization is tackled and therefore its impact on the productivity of firms operating under the institutional laws and setting of the country (Hanelt et al., 2020). Different countries have introduced different national plans to increase the investment of private sectors to retain competitiveness at the country level such as the "Manufacturing USA" and the "Industria 4.0" in Italy. The fourth research of this thesis is the following:

RQ4. *Are there different national approaches to digitalization in two major industrialized nations like Italy and the US that reflect institutional differences?*

1.3 Framework of analysis

1.3.1 Digitalization

Digitalization can be defined as the increased generation, analysis, and use of data through the adoption and implementation of digital technologies (e.g. sensors, RFID, machine vision, human-machine interfaces, software, platform) in the firm's product and inbound and outbound activities to increase internal efficiency and/or increasing customer offerings (Björkdahl, 2020).

Recent advancements in hardware (e.g. miniaturization, efficient batteries), open and standard communication protocols (e.g. MT Connect, OPC Unified Architecture), algorithms for data storage and processing (e.g. Hadoop, NoSQL), and algorithm advancement in the field of Artificial Intelligence (e.g. machine learning) (Figure 2) - have enabled the emergence of a new set of properties (e.g. traceability, virtualization, synchronization) of digital technologies that are different from the previous generation of information and communication technologies characterized by automation technologies and enterprise information systems (Hanelt et al., 2020). The so-called digital properties emerge by embedding computing capabilities in what used to be a non-digital artifact. In this vein, physical objects become programmable, addressable, senseable, memorizable, traceable, and associable (Y. Yoo, 2010).

The challenges and opportunities of digitalization have had a major impact on both business executives and policymakers. Digitalization has come to be seen as the fourth industrial revolution after the steam power, electricity, and automation that enable respectively the three preceding revolutions. Following the German government who first introduced the term "Industry 4.0", different countries have introduced national plans to increase the investment of private sectors to retain competitiveness at the country level e.g. in Italy "Piano Industria 4.0", in France "Industrie du Futur", Smart Manufacturing in the United States, etc.

Recent studies in the digitalization domain argue that there is a need to look at the unique properties or features of digital technologies to study how organizations need to adapt to technological implementation to increase cost performance (Cagliano, Canterino, Longoni, & Bartezzaghi, 2019; Cimini, Boffelli, Lagorio, Kalchschmidt, & Pinto, 2020). This point is echoed by organizational scholars who contend that digitalization should not view merely as the context for innovation, but increasingly as an *operant resource* that fuel innovation activities (Lusch & Nambisan, 2015). Nambisan et al., (2019) argued: "*it becomes imperative that studies incorporate characteristics innate to digital technologies as key explanatory factors in theorizing on the nature and process of innovation*". By bridging organizational literature (e.g. Kallinikos, Aaltonen, & Marton, 2013; Y. Yoo, 2010) and operation management literature (e.g. Culot, Nassimbeni, Orzes, & Sartor, 2020; Alejandro Germán Frank, Dalenogare, & Ayala, 2019), this thesis adapts and identifies the properties of two forms of digital technologies provided by Culot et al., (2020) physical-digital interface and network technologies.

The adoption of these two bundles of technologies pertains to two different stages of technology adoption which different maturity models and change management studies integrate albeit with different terminology (e.g. Agarwal & Brem, 2015; Schuh, Anderl, Gausemeier, ten Hompel, & Wahlster, 2017; D. R. Sjödin et al., 2018). In the first stage, physical-digital interface technologies (e.g. sensors, man-machine interfaces, machine vision, RFID, bar code) are introduced to collect real-time data and information from the shop floor and to support work processes (e.g. quality control, work instructions, monitoring and control of equipment). At this stage, the data generated from digitization technologies remains disconnected and in silos systems (Agarwal & Brem, 2015). In the second stage, as data increase in volume, variety, and velocity and opportunities to link these data increase (Cui, Kara, & Chan, 2020), firms engage in data integration efforts implementing network technologies (e.g. digital platforms, Manufacturing Execution Systems) that integrates shop-floor data with enterprise information system data (Cui et al., 2020; Schuh et al., 2017). These two stages of "digitization" and "integration" are recurring as the introduction of new physical-digital interface technologies triggers a new data integration process through the implementation of network technologies.

Physical-digital interface technologies include mainly a set of hardware components to identify each device univocally and in real-time (Kallinikos et al., 2013; Youngjin Yoo et al., 2012), tracing its status (and the change in it) as it moves along the production process (Lasi, Fettke, Kemper, Feld, & Hoffmann, 2014). In other words, they allow full **traceability** of product and process-related data. Traceability allows one to keep track of the six basic elements describing an event (When, Where, Who, What, How, and Why; e.g. when, by whom, where and what, how a product component was manufactured) (Pigni, Piccoli, & Watson, 2016). Embedded sensors can track product and process-related data during the manufacturing processes such as (depending on the type of processing e.g. lamination, molding, milling, etc.) workpiece temperature, environmental humidity, noise or acoustic emissions, vibrations, (tool and deformation) speed, (frictional, compressive and cutting) forces, etc. Connected to the traceability of physical objects, being them equipment or product components, is the second property of physical-digital interface technologies: *virtualization*. In this context, **virtualization** is defined as the ability to represent and simulate faithfully the behaviors of a physical device or a process (Bailey, Leonardi, & Barley, 2012). Virtualization can range from a simple approach, where only a set of data is gathered and make available in the virtual world, to more complex approaches, where physical objects or processes are simulated to predict their dynamics and behaviors (Tao & Zhang, 2017).

Network technologies include mainly a set of software components with the aim of quickly, reliably, and safely integrating vertically (across manufacturing stages i.e. from production planning, scheduling, maintenance, quality control to actual manufacturing) and horizontally (across product lifecycle stages i.e. from product development to sustainment) different streams of data in a unified corporate business system realizing the concept of digital thread and *extended enterprise* (Helu, Hedberg, & Barnard Feeney, 2017). Network technologies collect, integrate, and process sensory data from equipment and product components (both historical and real-time data), product data (e.g. design parameters from a CAD file, G-code file from a CAM file), production data (e.g. process order information), and business data (e.g. sales data from CRM system, accounting data from ERP, SCM, etc.) commonly managed in enterprise information systems such as MES, ERP, PLM, CRM (Cui et al., 2020; Helu et al., 2017). Network technologies enable ***accessibility,*** that is the ability to provide easy access to a heterogeneous and common pool of data coming from digitized devices and enterprise information systems such as sensory and enterprise data by different employees, departments, and business partners (i.e. customers, systems integrators, suppliers). Accessibility is similar to the concept of *communality* as long as the data access is provided through a common and integrated pool of data (Phang, Kankanhalli, & Tan, 2015). Network technologies enable synchronous communication between and among digitized devices and enterprise information systems (Fatorachian & Kazemi, 2018). The ***synchronization*** ensures that data in enterprise information systems are always updated and in real-time, thereby increasing opportunities for optimization and automation of the factory (Cui et al., 2020; Porter & Heppelmann, 2015). For instance, the process states of machines can be used for real-time production planning and scheduling tasks (Lenz, Wuest, & Westkämper, 2018). Since it would be challenging to perform one-to-one integration (if not impossible) among different business systems, network technologies leverage the data aggregation layer and require only one connection with the platform (Helu et al., 2017). In this vein, new software or applications (e.g. a warehouse management system) can be easily synchronized with digitized devices and other enterprise information systems (Helu et al., 2017).

1.3.2 Theoretical approach

The interplay between technology and organizational practices has been analyzed in the literature using theoretical lenses such as Socio-Technical System View (Trist, Higgin, Murray, & Pollock, 2013), Information-Processing View (Galbraith, 1974), the complementarity perspective (Milgrom and Roberts, 1995), affordances for organizing (Zammuto, Griffith, Majchrzak, Dougherty, & Faraj, 2007). These theories have been influenced by the Contingency Theory (Van de Ven, Ganco, & Hinings, 2013). The Contingency Theory is the main foundation for organizational design (Joseph, 2018), postulating that there is no best organizational arrangement (Van de Ven et al., 2013). The central tenet is designing arrangements of complementary and reinforcing organizational elements (internal fit) as well as aligning these to the environmental contingencies (external fit). Only when there is both an internal fit and external fit organizations can expect to increase performance. Seminal articles adopting a contingent-based perspective are those of: (i) Burns and Stalker (1961) who distinguished between two ideal types of organization: mechanistic and organic organizations as the opposite along a continuum depending on environmental uncertainty; (ii) Woodward (1965) who found significant variations in organizational structures, the span of control and use of written communication depending on the technology complexity that she classified into unit and small-batch, large batch, mass production, and process production. Eventually, environment, technology, and organizational size became the three legs of Contingency Theory (Zammuto et al., 2007). More recently, in the Industry 4.0 domain, some scholars revamp the contingency theory (Bokrantz, Skoogh, Berlin, Wuest, et al., 2020) and specifically using the socio-technical system view. Contingent variables range from technological complexity (measured as the number of technologies adopted and their integration) (Cagliano et al., 2019) to technological characteristics (Cimini et al., 2020).

However, the contingency theory present some limitations i.e. an exclusive focus on efficient factors, restricting free managerial choice, and neglecting the development of capabilities (Sousa & Voss, 2008). These limitations mean the Contingency Theory does not always prescribe deviations from contingency-determined patterns (Sousa & Voss, 2008). To address these, researchers propose to adopt additional theories (Sousa & Voss, 2008) and novel methods (Van de Ven et al., 2013). This thesis adopts additional theories (Sousa & Voss, 2008), and in particular: the Information-Processing View (IPV) (Galbraith, 1974), the Organizational Sensemaking (OS) (K. E. Weick, 1995), the Knowledge-Based View (KBW) (Grant, 1996). and the Transaction Cost Economics (TCE) (Williamson, 1985)

The aim of this thesis is not to provide a theoretical contribution to those theories that are well-consolidated but to use these theories to understand the phenomenon of digitalization that is when and how digitalization increases cost performance. In this vein, this thesis adopts two approaches: theoretical contextualization and phenomenon-based research (Ketokivi & Mantere, 2010; von Krogh, 2018).

The theoretical contextualization approach is the application of multiple theories as an integral part of the reasoning and specifically in the inference process (Bokrantz, Skoogh, Berlin, Wuest, et al., 2020; Ketokivi & Mantere, 2010). Through this abductive reasoning approach, empirical results and theories are investigated simultaneously to provide the best explanation for the occurrence of specific results (i.e. inference to the best explanation). In this vein, the research effort was directed to provide the best explanation of the empirical results based on existing theoretical prescriptions that is the ability of a theory to explain the results regardless of the measurement of the underlying key theoretical concepts (Ketokivi & Mantere, 2010). In this thesis, the inference process is when and how digitalization and practices jointly affect cost performance.

Phenomenon-based research is the study of the novel and emergent phenomena rather than theory testing (Von Krogh, Rossi-Lamastra, & Haefliger, 2012). A phenomenon can be defined “as regularities that are unexpected, that challenge existing knowledge (including existing theory) and that are relevant to the scientific discourse (Von Krogh et al., 2012; pp. 278). Phenomenon-based research aims to “capture, describe and document, as well as conceptualize, a phenomenon so that appropriate theorizing and the development of research designs can proceed” (Von Krogh et al., 2012; pp. 278). The phenomenon-based research has some advantages including a better understanding of emergent phenomena, the alignment of practical relevance and academic rigor, the development of new theories by (i) referring to existing theory (ii) integrating, modifying, or adapting exiting theories (iii) or inductively generate new theoretical concepts (Von Krogh et al., 2012). Phenomena can be of different types arising from natural to social science. In the management research, the focus is on social and organizational phenomena including, for instance, open-source software, transnational corporations (Von Krogh et al., 2012), digitalization, and artificial intelligence (a subset of digitalization) (von Krogh, 2018).

Phenomenon-based research and theoretical contextualization share the abductive reasoning approach (Bamberger, 2018; Bokrantz, Skoogh, Berlin, & Stahre, 2020). The thesis uses this approach by using a set of management theories to describe the organizational and social phenomenon of digitalization (Bamberger, 2018).

Figure 1 provides the research framework for this thesis.

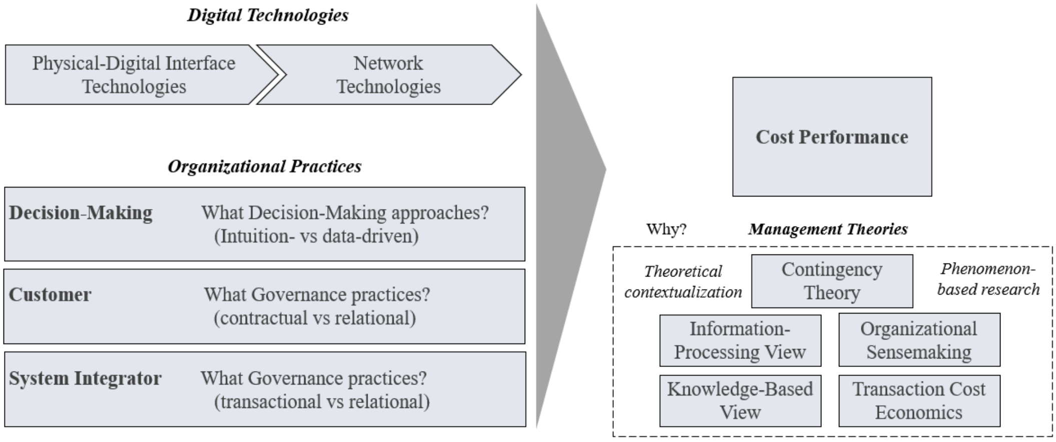

Figure 1. The research framework of the thesis

1.4 Empirical research setting

To investigate the research questions, this thesis focuses on the **Italian automotive component industry**. The choice of the automotive industry is relevant for at least two main reasons. First, the study of automotive is of great value per se given that it has a high employment share and account for a greater part of the GDP of most advanced countries. For instance, in Italy, the turnover of the automotive industry accounts for 5,9% of the Italian GDP (Barazza & Coccimiglio, 2019). Second, the automotive industry is subject to greater competitive pressure than other industries, which has to deliver complex industrial products subject to high levels of international standards, quality, and efficiency (Liao, Deng, Liao, & Zhang, 2020; Qamar, Hall, & Collinson, 2018) which determine a continuous need to innovate production process to stay ahead of the competition. Therefore, it is easier that firms in this industry are earlier adopters of new digital technologies (PwC, 2018) and thus to study technology-enabled organizational transformations.

The research method used a mixed-method approach involving the analysis of both quantitative and qualitative data. Concerning quantitative data, the thesis used a multi-respondent and comprehensive quantitative survey issued to human resource, plant, and sales managers of the entire population of the Italian automotive supply firms between March 2019 and February 2020. The survey was conducted with the support of ANFIA (the major Italian industrial automotive association) and the Chambers of Commerce of Turin. The unit of analysis of the survey is the plant. A total of 101 auto suppliers' plants participated in the survey, mainly SMEs operating as tier 1 (40%) and tier 2 (25%), constituting a sample representative of the population in terms of plant size, geographical region, and supply chain position. Response rates were 5% over the population and 18% over the sampling frame of firms that were provided by ANFIA and the Turin Chambers of Commerce. A parallel and fully comparable survey of US firms active in the automotive sector has been performed by Case Western University, New York Stern University, and local automotive associations.

The quantitative survey was accompanied by fourteen case studies undertaken in the Turin metropolitan area. The cases have been performed in this area because several automotive suppliers are located here working direct or indirect customers of FCA and the proximity to German carmakers and suppliers. The case studies allow investigating more deeply organizational practices as firms adopt digital technologies.

1.5 Research findings and contributions

1.5.1 Decision-making approaches

Concerning **decision-making**, this thesis starts with the assumption that two main decision-making approaches can be found in manufacturing firms: intuition-driven decision-making and data-driven decision-making. The **intuition-driven decision-making approach** refers to affectively charged judgments that arise through rapid, non-conscious, and holistic associations (Dane & Pratt, 2007), By contrast, the **data-driven decision-making** involves quantitative assessment, decomposition, and recombination of data and information that arise through slow, conscious and sequential associations (Julmi, 2019). In principle, there is no superior decision-making approach (Flores-Garcia et al., 2019) as the optimal approach to be used depending on the context i.e. on the structuredness of events upon which decisions are made. The structuredness of an event refers to the extent to which events can be decomposed and approached sequentially by applying objective, widely accepted decision procedures and rules, and by relying on unequivocal interpretations (Flores-Garcia et al., 2019). From this definition, it follows that two main variables describe the structuredness of an event: equivocality and analyzability (Flores-Garcia et al., 2019). **Equivocality** refers to numerous and conflicting interpretations about an event, and it is associated with problems such as a lack of consensus, understanding, and confusion. Analyzability refers to the degree to which it is possible to use computational, objective rules and procedures as opposed to personal judgment and experience (Flores-Garcia et al., 2019). **Analyzability** can be further decomposed into detectability (the extent to which is possible to capture one or more 5W+H of an event), measurability (the extent to which such 5W+H can be empirically assessed), and interpretability (the extent to which a firm can achieve the needed understanding of the event) (Pigni et al., 2016). This thesis asserts that the adoption of physical-digital interface technologies, and their subsequent interconnection through network technologies, can respectively increase the analyzability and reduce the equivocality of events.

Under these conditions, to exploit the value of digital technologies and increase cost performance, this thesis found a data-driven decision-making approach widely diffused in the plant is a precondition to increase cost performance. Through some case studies, this thesis found that to diffuse a data-driven decision-making culture companies should invest in lean production, assigning to management measurable and attainable objectives, and training employees in data analysis and analytical skills.

1.5.2 Governance practices with customers

Concerning governance practices with customers, this thesis starts with the consideration that contractual and relational governance mechanisms are considered the most effective mechanisms for successful inter-organizational relationships in supply chains (G. Cao et al., 2015; L. Poppo & Zenger, 2002). The opportunities offered by digitalization allow companies to embrace new approaches to manage and govern supply chain processes with novel technological and analytical methods, thereby creating incentives for significant performance improvements and added value (Büyüközkan & Göçer, 2018). The results reveal that the properties of synchronization and accessibility, which are ensured by network technologies, and contractual governance - in particular in the long-term dimension - are complementary, while virtualization and traceability, enabled by physical-digital interface technologies, are complementary with relational governance in the suppliers' effort to increase cost performance.

Physical-digital interface technologies, thanks to their ability to create real-time information transparency, encourage the development of trust between parties and provide a digital means for collaboration with the customers to pinpoint localized production problems or to find improvement opportunities. On the other hand, network technologies enable full and real-time transparency of process-related information and require long-term contractual governance that signals the commitment of suppliers to not exploit such an integration opportunistically, since it increases the visibility of customers on supplier's processes. This thesis speculates that in the case of seamless integration of process information, it is not enough to have relational norms and trust and that a formal and explicit shared commitment is also required.

Conversely to what was expected, the technologies that enable synchronization and accessibility do not appear to be linked to relational governance. This result is counter-intuitive, considering the growing literature on how the increased connectivity and seamless integration of information enhance further sharing and cooperation that would eventually increase the cost performance of suppliers (e.g. Fatorachian & Kazemi, 2020). Nevertheless, this can be interpreted as an enhanced capability of suppliers to prevent possible forms of opportunistic behavior, due to a closer dependency on customers (as an "indirect effect" of integration), as well as a way of maintaining selected information asymmetries and of leaving space for flexibility in production settings. Although a collaborative relationship allows both parties to obtain benefits, a conflicting element is inevitably embedded in the inter-organizational relationship, especially in the automotive supply chain sector, due to the tendency of firms to protect individual competitive advantages, such as cost performance (Huang, Han, & Macbeth, 2020).

1.5.3 Governance practices with system integrators

To make digitalization effective inside the factory, this thesis found that - at an increasing rate of technology complexity, customization levels, and novelty of the two different forms of digital technologies – manufacturing firms should rely on forms of relational governance practices based on co-creation and continuous collaboration with technology partners like system integrators that would allow the reduction of transaction costs but more importantly the sharing of technological and domain knowledge and process of sensemaking of new technologies.

The implementation of physical-digital interface, with properties of virtualization and accessibility, does not require systemic changes into manufacturing infrastructures as they touch only isolated point of the factory (e.g. equipment, production line, etc.); they require limited customization to be operative by relying on plug-and-play installation; they are better-known technologies since they exist in the manufacturing domain as operation and automation technologies since decades. Therefore, the lower levels of complexity, customization, and novelty of these technologies determine lower levels of interpretative uncertainty. As a result, this thesis found that when firms adopt only physical-digital interface technologies their relationship with system integrators can be based on market-based or transactional-based interactions which are relative only to the purchase and installation of the technologies. The combination of technology adoption and transactional governance practice was found to be positively related to cost performance.

By contrast network technologies require the integration of data flows and the connection of equipment and information systems involving significant integration and systemic changes in the technological infrastructure of firms; they also require significant customization level to adapt network technologies with systems and processes already present in the firms; they are based on novel architectures such as Service-Oriented Architecture, new technologies such as cloud computing and data lakes that are relatively new to manufacturing firms. Therefore, the higher levels of complexity, customization, and novelty of these technologies determine high levels of interpretative uncertainty and in turn, the relationship with system integrator should be based on relational-based governance such as co-creation and continuous collaboration to have a successful project implementation and there more probabilities to increase cost performance. Moreover, a system integrator can become active partners in supporting the firms in reducing production costs by offering them tailored data analytics services to pinpoint production problems and provide solutions. The combination of physical-digital interface and network technologies adoption and relational-based governance practices of co-creation and continuous collaboration was found positively related to cost performance.

1.6. Conclusions

Prior research has focused on the complementarity of information and communication technologies and organizational practices, overlooking the properties of a new generation of digital technologies (E. Brynjolfsson & Hitt, 2000; Hanelt et al., 2020). While following this stream of research, this thesis contributes to a more recent literature stream that examines the impact of new digital technologies on organizational performance (e.g. Lorenz et al., 2020; Martínez-Caro et al., 2020; Trantopoulos et al., 2017). The first contribution is the identification of the properties of the two forms of physical-digital interface technologies and network technologies previously identified (Culot et al., 2020). Future research can use the properties of these two technologies to investigate other organizational issues such as competence and skills development with training practices, privacy issues related to the control of workers' activities, new mechanisms for knowledge search and recombination.

These results of this thesis point out how complex is for manufacturing firms to make decisions about digitalization investments at the process level and to enhance cost performance. On the one hand, they have to invest in different and highly specific sets of digital technologies and, on the other hand, to change decision-making approaches, to manage their interplay with the governance mechanisms with technological partners and customers.

1.6 Thesis Structure

This thesis is structured as follows. Chapter 2 discusses digitalization, digital process innovation, and provides the results of a literature review on the properties of digital technologies. Chapter 3 briefly illustrates the management theories that will be used in this thesis. Chapter 4 illustrates the automotive industry as the research setting of this thesis providing the rationales of focusing on the automotive industry, the main industry characteristics, the main digitalization trends along with a description of the research method. These three chapters are a preamble to the investigation of the research questions in the following chapters. Chapter 5, Chapter 6, and Chapter 7 discuss the interplay between digital technologies on hand, and decision-making approaches, governance practices with customers, and governance practices with system integrators on the other hand, on firms' effort to increase cost performance. Chapter 8 provides a comparative analysis between Italy and the US. Chapter 9 provides a summary of the research findings, the theoretical contributions, and managerial recommendations.

Chapter 2

Literature review on digitalization

2.1 Introduction

This chapter provides the definitions of digitalization and related terms (e.g. Industry 4.0), the digital technologies that are part of the digitalization phenomenon, the challenges of implementing digital technologies in manufacturing organizations (i.e. digital process innovations), and discuss the properties of two subsets of digital technologies: physical-digital interface technologies and network technologies. Along with the next chapter, this chapter provides a preamble to the following parts of the thesis. The method used in this chapter is a systematic literature review on two literature streams that investigate the implications of digital technologies from different perspectives: organizational and information system literature on one hand and operations management literature on the other hand. Both literature streams agree that there is a need to look at the unique properties or features of digital technologies to study how organizations need to adapt to technological implementation to increase cost performance (Cagliano et al., 2019; Cimini et al., 2020; Lusch & Nambisan, 2015). The review process started with a search query on the SCOPUS database limiting to peer-reviewed academic articles (excluding conference papers and non-academic articles) using both keywords from organizational literature (e.g. digitalization, digitization, digital technologies) and operation management literature (e.g. Industry 4.0, Smart Manufacturing, Industrial Internet) covering the period until September 2020 (Table 1). The outcome of these search query results in **861 papers**. After reading the abstract of each article, the papers were grouped into two subsets referring to physical-digital interface technologies and network technologies while others not relevant were excluded. These two subsets were later expanded with two other queries that the use of some specific keywords (e.g. internet of things, IoT, digital twin for physical-digital interface technologies; digital infrastructure, digital platform, digital thread for network technologies) that have been retrieved after reading the most relevant papers of the first search query (Table 1). However, at this stage, the keywords "properties" and "principles" were excluded to include the papers that do not explicitly review these concepts but provides the characteristics of these technologies (Table 1). Furthermore, a set of other papers have been retrieved looking at the reference of the papers and added to these two subsets. Compared to the literature review performed by Culot et al., (2020), this thesis adds the analysis of organizational and information system literature where the discussion of digital properties is much more consolidated.

Table 1. Literature review scope and methodology

Field	Value
Subject area	Business; Management and Accounting; Economics, Econometrics and Finance; Decision Science; Engineering
Source type	Journal
General digitalization literature	
Keywords	(("digit* technolo*" OR "digitalization" OR "Industr* 4.0" OR "Smart Manufacturing" OR "Industrial Internet") AND ("propert*" OR "principle*"))
Output	861 papers
Physical-digital interface technologies literature	
Keywords	("digit* technolo*" OR "digitalization" OR "Industr* 4.0" OR "Smart Manufacturing" OR "Industrial Internet") AND ("internet of things" OR "IoT" OR "digital twin")
Output	460
Network technologies literature	
Keywords	("digit* technolo*" OR "digitalization" OR "Industr* 4.0" OR "Smart Manufacturing" OR "Industrial Internet") AND (“digital infrastructure” OR “digital platform” OR “digital thread”)
Output	138

This chapter is structured as follows. In section 2.2, the digitalization phenomenon is defined, followed by a discussion of the term “Industry 4.0” which is widely used among practitioners. Since this thesis uses the Italian automotive industry as the setting of this research, section 2.2.1 illustrates briefly the Industry 4.0 National Plan conceived by the Italian Ministry of Economic Development at the end of 2016. Section 2.3 provides the challenges of digital process innovation. This chapter concludes with a discussion of the properties of the two forms of digital technologies identified in section 4.4.

2.2 Understanding digitalization

Digitalization can be defined as the increased generation, analysis, and use of data through the adoption and implementation of digital technologies (e.g. sensors, RFID, machine vision, human-machine interfaces, data lakes, data warehouse) in the firm’s product and inbound and outbound activities to increase internal efficiency and/or increasing customer offerings (Björkdahl, 2020).

Recent advancements in hardware (e.g. miniaturization, efficient batteries), open and standard communication protocols (e.g. MT Connect, OPC Unified Architecture), algorithms for data storage and processing (e.g. Hadoop, NoSQL), and algorithm advancement in the field of Artificial Intelligence (e.g. machine learning) (Figure 2) - have enabled the emergence of a new set of properties (e.g. traceability, virtualization, synchronization) of digital technologies that are different from the previous generation of information and communication technologies characterized by automation technologies and enterprise information systems. The so-called digital properties emerge by embedding computing capabilities in what used to be a non-digital artifact. In this vein, physical objects become programmable, addressable, senseable, memorizable, traceable, and associable (Y. Yoo, 2010).

Hardware
- Miniaturization and cost reduction of hardware (e.g. Arduino, Raspberry Pi)
- Computational power (processing and storage)
- Low-energy battery

Connectivity and Standards
- Open communication protocols (e.g. MTConncect, MQTT, OPC-UA)

Software
- Algorithms for data storage and processing (e.g. open source like Hadoop, NoSQL)
- Algorithmic advancement (e.g. machine learning, deep learning)

Figure 2. Inter-connected trends

The challenges and opportunities of digitalization have had a major impact on both business executives and policymakers. Digitalization has been recognized as the fourth industrial revolution after the steam power, electricity, and automation that enable respectively the three preceding revolutions. Following the German government who first introduced the term “Industry 4.0”, different countries have introduced national plans to increase the investment of private sectors to retain competitiveness at the country level e.g. in Italy “Piano Industria 4.0”, in France “Industrie du Futur”, Smart Manufacturing in the United States, etc.

From a technical point of view, **Industry 4.0** refers to “the digitalization of the manufacturing sector, with embedded sensors in virtually all product components and manufacturing equipment, ubiquitous cyber-physical systems, and analysis of all relevant data” (McKinsey Digital, 2015). It is composed of three main dimensions: (1) digitalization of manufacturing processes to enable decentralized, data-driven decision-making; (2) smart manufacturing through cyber-physical systems that provide a virtual representation of the factory and permit real-time monitoring and self-controlled production systems; (3) inter-company connectivity between suppliers and customers within the value chain that increase information sharing and transparency (Arcidiacono, Ancarani, Di Mauro, & Schupp, 2019; Müller et al., 2018)

The fact a digital revolution is for the first time is predicted rather than being observed raises critics about the clarity of the phenomena with multiple definitions, different technologies, and unclear boundaries. In this respect, Reischauer (2018) argues that Industry 4.0 represents a policy-driven innovation discourse aimed at institutionalizing a Triple Helix model of collaboration between government, academia, and enterprises. In this respect, an industrial revolution is not shaped by technological advancements only, but it is also an outcome of social and political factors (Reischauer, 2018). The role of such policy-driven innovation discourse is to *legitimate* the innovation activities of actors under the direction of digitalization (Reischauer, 2018). For instance, by establishing pilot lines and research programs in universities and research centers, an enterprise may do the same because its actions are now legitimate by the external environment. While it is yet to be seen if these policy-driven initiatives will determine a revolution, it is unquestionable that these policies have determined an increase of investment in digital technologies in all manufacturing industries (Bratta, Romano, Acciari, & Mazzolari, 2020). Crucially, the realization of a revolution that manifest in a leap of productivity in all the economy occurs when organizations re-arrange organizational and managerial practices. Remarkably, it took 30 years after the first introduction of energy into factory to manifest the second industrial revolution characterized by mass production because firms needed a new set of workers equipped with new skills and because previous equipment, previously located closed to source of power, had to be amortized before being replaced.

2.2.1 The Italian national plan "Industria 4.0"

An example of a policy-driven innovation discourse is the "Piano Industria 4.0" (hereafter Industry 4.0 National Plan) introduced at the end of 2016 by the Italian Minister of Economic Development. The Industry 4.0 National Plan had three main pillars/objectives: (i) increase investments in digital technologies through fiscal incentives; (ii) raise awareness and competence through new public-private partnership (e.g. digital innovation hubs and competence center) and strengthening of technical high institutes; (iii) advancing the technological infrastructure via capillary diffusion of ultra-wideband communication infrastructure and promotion of technological standard (MEF et al., 2018).

Among the three objectives, the first received the greatest attention from policymakers and entrepreneurs mainly due to the delay of policymakers to set policies for the establishment of competence centers, which have started to operate only recently. The key measure was an increase of depreciation allowance, i.e. the amount a firm can reduce its taxable income, by a percentage of the 140% (rather than 100%) on of the purchase cost of fixed capital (e.g. machinery, robots; the so-called hyper-depreciation) and 250% on the purchase cost of software and connectivity technologies (i.e. super-depreciation) (Perani, Costa, & De Santis, 2019).

This led, in the first year, to a €7 Bn investment connected to the hyper-depreciation measures, out of which 83% originated in manufacturing (Bratta et al., 2020). The majority of recipient firms were SMEs located in the Northern regions (Bratta et al., 2020). A criticism often leveled at the Industry 4.0 National Plan is its focus on technological investments while the policy for the development of competencies (e.g. training paths in competence centers) had been considered only later. This advanced the idea the main outcome of the plan has been in substituting old machinery or retrofitting existing equipment (Perani et al., 2019). While this could have a short-term impact in reduced investment costs, such an adoption process may be accompanied by a limited or partial recognition of the long-term benefits ignited by the adoption of digital technologies. Despite the critics, the Industry 4.0 National Plan has been an enabler of investments in digital technologies. Recent research by the Italian Ministry of Economy and Finance found that around 85% of firms that benefit from hyper-depreciation in 2017 had never invested in digital technologies before (Bratta et al., 2020). The same research also found that this investment had positive net effects on employment for younger individuals and those blue-collar in medium-skills occupations (Bratta et al., 2020). It has also the merit to shift the focus of politics on the industrial policy after a long time. However, it remains to be seen if competence centers and digital innovation hubs will favor the development of competence of Italian firms, including automotive suppliers.

2.3 Digital process innovation

As far as digital technologies are implemented to improve processes (and not product), digitalization involves many process innovations. Process innovation is an important component for the competitiveness of firms because it helps the firm achieve greater operational efficiencies, improve product features, and quality (Womack, Jones, & Roos, 1990). **Process innovation** refers to “the implementation of new or significantly improved production or delivery methods. This includes significant changes in techniques, equipment and/or software” (OECD. et al., 2005, p. 9). The exemplary process innovations are the assembly line introduce by Henry Ford to produce the Model T, which paves the way for mass production, and lean production (Womack et al., 1990). Indeed, not all the process innovation have a similar impact but occur in factories through small-scale changes in the methods of production, often involving routine operational improvements (Reichstein & Salter, 2006). Reducing the time for prototype development, designing a new plant layout, purchasing and installing new equipment, integrating new and existing machinery, conducting pilot runs are all examples of process innovations (Trantopoulos et al., 2017). There is an agreed consensus that process innovation to be effective need changes in structure, management, and work practices (Davenport, 1993). Applications of the steam engine, for instance, required significant reorganization of the factory production (Ettlie & Reza, 1992). The outcomes of process innovation include reducing time-to-market, improving product quality, production flexibility, and delivery reliability (Flores-Garcia et al., 2019; Trantopoulos et al., 2017), but scholars tend to agree that process innovation activities aimed ultimately at lowering production cost, thus making cost reduction a key operationalization (Trantoupolos et al., 2017)

The current generation of process innovation is increasingly digital, driven by the application of digital technologies (Lorenz et al., 2020; D. R. Sjödin et al., 2018). Digital process innovation is at the core of digitalization and Industry 4.0. Fichman et al., (2014) defined **digital process innovation** as *significantly new (from the perspective of the adopter) ways of doing things in an organizational setting that are embodied or enabled by digital technologies.*

Digital process innovation is often highly problematic due to unique properties of digital innovations (Henfridsson & Bygstad, 2013; Youngjin Yoo et al., 2012), which require recombination of tacit and explicit knowledge, complex problem solving, learning by trial and error, and systemic changes into several components of a production system (D. R. Sjödin et al., 2018; Trantopoulos et al., 2017). The implementation of digital process innovations may lead to unanticipated technological challenges, new skills for the operating personnel and significant change in the work practices (Trantopoulos et al., 2017). These complexities make digital process innovations a highly challenging and risky effort that extends well beyond the introduction of digital technologies (D. R. Sjödin et al., 2018).

2.4 Properties of digital technologies

Digital technologies come in many features, including computing, communication, connectivity, and data processing capacities (Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013). Recent literature reviews argue that there is the need to limit and focus on specific technologies (Oesterreich & Teuteberg, 2016; Pfohl, Yahsi, & Kurnaz, 2015) and to group them concerning their purposes and characteristics (Cagliano et al., 2019; Cimini et al., 2020). In a similar vein, organizational scholars argue that digitalization should not view merely as the context for innovation, but increasingly as an *operant resource* that fuels innovation activities (e.g. Lusch & Nambisan, 2015). Nambisan et al., (2019) argue "*it becomes imperative that studies incorporate characteristics innate to digital technologies as key explanatory factors in theorizing on the nature and process of innovation"*. By bridging organizational literature (e.g. Kallinikos et al., 2013; Youngjin Yoo et al., 2012) and operation management literature (e.g. Culot et al., 2020; Alejandro Germán Frank et al., 2019), this thesis aims to identify the properties of digital technologies in the manufacturing context. Some authors discuss the principal features of digital technologies under Industry 4.0. Hermann et al., (2016) discuss four design principles: interconnection, information transparency, technical assistance, and decentralized decisions. Mittal et al., (2019) provide an exhaustive list of characteristics which they group in compositionality, context awareness, heterogeneity, interoperability, and modularity. However, these characteristics are mainly at a macro level and they do not distinguish the property of different forms of digital technologies. To fill this gap, this thesis focus on two forms of digital technologies: physical-digital interface technologies and network technologies (Culot et al., 2020). These will be discussed in the following paragraphs along with their properties.

2.4.1 Physical-digital interface technologies

From a technological point of view, implementing digital process innovations requires data access, computation, and communication technologies with acting hardware components to bridge the physical reality of equipment and product components with the cyber-space (Balsmeier & Woerter, 2019; Culot et al., 2020). This subset includes the Internet of Things and the Cyber-Physical Systems (Culot et al., 2020). However, these technologies are quite generic representing mainly concepts rather than actual technologies. The base technologies of this subset include sensors, tracking technologies (such as RFID, bar codes, smart label), machine vision and visualization technologies (such as augmented and virtual reality, display touch, wearables)

Physical-digital interface technologies include mainly a set of hardware components to identify each physical device univocally and in real-time (Kallinikos et al., 2013; Youngjin Yoo et al., 2012), tracing its status (and the change in it) as it moves along the production process (Lasi et al., 2014). In other words, they allow full *traceability* of product and process-related data. ***Traceability*** is defined as "*the ability to discover the history of decision in the [product] lifecycle; to control the quality of data, products, and processes; and to understand the relationship between assets*" (T. D. Hedberg, Krima, & Camelio, 2019; p. 1). Traceability allows to keep track of the six basic elements describing an event (When, Where, Who, What, How and Why; e.g. when, by whom, where and what, how a product component was manufactured) (Pigni et al., 2016) As far as product components are concerned (which include final products, assemblies or single parts), they become *information carriers* as they contain information of the entire lifecycle phases (Anderl, 2015). For instance, machine vision technologies can track product components as they move along the production lines, especially in those situations in which it is difficult to attach other identification technologies (e.g. in harsh working environments) (Anderl, 2015). Machine-embedded and machine vision sensors can monitor in-process quality parameters and end-of-line product quality and store these data in databases allowing full traceability of product quality (Moru & Borro, 2020). Similarly, tracking technologies (such as RFID, NFC, bar codes and smart labels) enables the *traceability* of product components useful for logistic and supply chain such as real-time inventory status and location (Anderl, 2015;

Halawa et al., 2019). The same discussion applies also to machines, tools, dies, and other equipment where embedded sensors can track product and process-related data during the manufacturing processes such as (depending on the type of processing e.g. lamination, molding, milling etc.) workpiece temperature, environmental humidity, noise or acoustic emissions, vibrations, (tool and deformation) speed, (frictional, compressive and cutting) forces, etc. The traceability of objects has a twofold implication. On the one hand, traceability guarantee that the component is produced according to the specifications providing a safety legal measures in case of product issues. On the other hand, if product issues arise the traceability of product components but also of equipment allow to isolate the related component of the same lot and then to undertake recall actions (Alejandro Germán Frank et al., 2019), understand the root cause of quality issues (e.g. machine operating at a lower speed, excessive tool wear, an operator not well-trained etc.), and prevent future production disturbances.

Connected to the traceability of physical objects, being them equipment or product components, is the second property of physical-digital interface technologies: *virtualization*. In this context, ***virtualization*** is defined as the ability to represent and simulate faithfully the behaviors of a physical device or a process (Bailey et al., 2012). Virtualization can range from a simple approach, where only a set of data is gathered and make available in the virtual world, to more complex approaches, where physical objects or processes are simulated to predict their dynamics and behaviors (Tao & Zhang, 2017). Virtualization is the ability to create a *digital twin* of a physical device or process (Tao et al., 2018). Concerning product components, virtualization means that data may not only related to nominal geometry but also tolerances, material specifications, component list, process specifications, and inspection requirements thereby providing a direct link with manufacturability and quality inspection (T. Hedberg, Lubell, Fischer, Maggiano, & Feeney, 2016). Like traceability, virtualization apply also to machines, tools, dies, and other equipment. For instance, machine vision can be applied to the condition monitoring of tools degradation in machining processes (Lins, de Araujo, & Corazzim, 2020).

Virtualization enables processes of understanding, interacting, and predicting the behavior of physical objects or processes. From operating *through* virtual models to control machines and production processes, physical-digital interface technologies increasingly allow operating *within* digital models to enable the understanding, study, and experimentation. On the other hand, virtualization determines an increase of cognitive overload, an increase of "informated" work, and may cause a lack of trust in digital models or representations (Bailey et al., 2012). As far as machine tools (i.e. a machine that cut, shape, finish or other rigid materials), the most common application of virtualization in the shop-floor is predictive maintenance (Bokrantz, Skoogh, Berlin, Wuest, et al., 2020), Literature shows that the more data sources are used to retrieve different kind of data (e.g. RFID tags and readers, power meters, accelerometers, acoustic emission sensors, coordinate measuring machines, etc.), the more the digital twin is a faithful representation of the physical process and therefore the better the ability to predict the maintenance requirements (C. Liu, Vengayil, Zhong, & Xu, 2018). Concerning product components, the most direct application of virtualization is the prediction of product quality. Indeed, maintenance and product quality are related and it easy to find applications that estimate both (Lenz et al., 2018).

Taken together, the traceability and virtualization properties of physical-digital interface technologies allow to access and collect a range of process- and product-related data that can be later processed by employees to troubleshoot root causes or predict the occurrence of quality and equipment issues. The two properties increase the *analyzability* of events and problems (i.e. the degree to which problems or activities require objectives procedures as opposed to personal judgment or experience) (Flores-Garcia et al., 2019). Indeed, the data generated from multiple sources is ready for univariate and multivariate analysis (e.g. correlation, clustering, regression) and machine learning algorithms could be implemented to predict the occurrence of production problems (e.g. quality issues, equipment breakdown).

2.4.2 Network technologies

Once the necessary data on physical devices have been collected, network technologies provide the necessary (and ideally seamless) integration to make the product and process data analyzable, accessible, and easily exchanged within and across the organizational boundaries (Culot et al., 2020). Network technologies enable the **digital thread** concept defined as the process of linking disparate systems across the product lifecycle and throughout the supply chain (T. Hedberg, Feeney, Helu, & Camelio, 2017). Network technologies ensure an improved physical-to-digital and digital-to-physical transfer capabilities (Fatorachian & Kazemi, 2020), with virtual prototypes and design requirements in the digital-space that are bridged with the products to be realized, the materials to be handled and the operational processes to be managed, with a multiplicity of business partners and employees having access to them.

Network technologies include mainly a set of software components with the aim of quickly, reliably, and safely integrating vertically (across manufacturing stages i.e. from production planning, scheduling, maintenance, quality control to actual manufacturing) and horizontally (across product lifecycle stages i.e. from product development to sustainment) different streams of data in a unified corporate business system realizing the concept of digital thread (see above) and *extended enterprise* (Helu et al., 2017). Network technologies collect, integrate, and process sensory data from equipment and product components (both historical and real-time data), product data (e.g. design parameters from a CAD file, G-code file from a CAM file), production data (e.g. process order information), and business data (e.g. sales data from CRM system, accounting data from ERP, SCM, etc.) commonly managed in enterprise information systems such as MES, ERP, PLM, CRM (Cui et al., 2020; Helu et al., 2017). It should be noted here that many of these technologies exist in manufacturing for decades. However, these systems have two main drawbacks (Cui et al., 2020). First, they lack sensory data and therefore are not able to track real-time changes in the factory and the supply chain (Fatorachian & Kazemi, 2018). Second, they are developed by multiple vendors using different interfaces and protocols resulting in siloed data sources and information (Fatorachian & Kazemi, 2018; Helu et al., 2017). Moreover, as a new system is introduced point-to-point integrations with the other systems are necessary. Network technologies advance a new era for enterprise information systems through the capture of real-time and historical shop-floor data and system integration enabled respectively by new or improved physical-digital interface technologies, standards, and protocols, (e.g. MTConnect, OPC UA), *consumerization* of digital technologies (Bygstad, 2017) on the one hand; new data infrastructures (Helu et al., 2017; Lenz et al., 2018), big data technologies (e.g. Hadoop, Spark) (Cui et al., 2020) and cloud computing on the other hand. In this respect, network technologies advance the integration between *lightweight* IT and *heavyweight* IT (Bygstad, 2017), between *operational* and *information technologies* (Agarwal & Brem, 2015; Lenz et al., 2018)

In a data-driven manufacturing organization, the data infrastructure should ensure access to their systems just like a user surfs the internet through a web browser or mobile applications (e.g. production manager, maintenance employees, customers, etc.). Related to this is the need to support multiple users with different needs and viewpoints. Second, the data infrastructure has to deal with the 3Vs challenges of big data: Volume (terabytes of data size), Velocity (ingesting or processing data in streams or batches, in real-time or non-real-time), Variety (structured, semi-structured, unstructured data coming from different sources) (Cui et al., 2020). To accomplish these challenges, new data infrastructures are proposed in the literature such as 4-tiers and Service-Oriented Architecture (SOA) architectures (Fatorachian & Kazemi, 2018; Helu et al., 2017), hybrid data infrastructure with data lakes and data warehouses at their centers (Cui et al., 2020; Fang, 2015), new conceptual models (Tao & Zhang, 2017), big data and cloud computing technologies (Coronado et al., 2018; Cui et al., 2020). **Data lakes** are defined as firm-wide data platforms for storing and analyzing different sources of unstructured data in their native formats (Fang, 2015). **Data warehouses** are defined as enterprise-wide data management for collecting, pre-processing, and analyzing the different sources of mainly structured data (Fang, 2015). Unstructured data are any kind of data that cannot be arranged in rows and columns without losing inner information. Good examples are sensor readings, CAD models, textual documents, videos, images. Structured data are considered any kind of data that can be arranged into columns and rows without losing information. Good examples are computer data logs, excel files, CSV files, ERP data. It is estimated that the average information system contains 15% structured data and 85% unstructured (Cui et al., 2020). **Cloud computing** can be defined as a technology for on-demand network access to a shared pool of configurable computing resources (e.g. networks, servers, storage, applications, and service) that can be provided with minimal management effort or service provider interaction (Mell & Grance, 2011).

While the technical characteristics of data architectures, data lakes, data warehouse, cloud computing, and big data technologies are out of the scope of this paper, what is important to note here is the increased tendency of manufacturing firms to use network technologies (a collection of the aforementioned software technologies) to collect sensory and enterprise data from different sources into a unified system departing from the traditional siloed perspective among different manufacturing systems (Björkdahl, 2020; Cui et al., 2020; Fatorachian & Kazemi, 2018; Helu et al., 2017; Lenz et al., 2018; D. R. Sjödin et al., 2018).

Some commercial examples of network technologies are provided in the appendix (Table A1). In the literature, some open-source approaches are proposed, especially suitable for SMEs (e.g. Coronado et al., 2018; Kwon, Monnier, Barbau, & Bernstein, 2020; Lenz et al., 2018).

Having discussed briefly the core technologies and data infrastructure, the properties of network technologies are provided below. Network technologies enable ***accessibility,*** that is the ability to provide easy access to a heterogeneous and common pool of data coming from digitized devices and enterprise information systems such as sensory and enterprise data by different employees, departments, and business partners (i.e. customers, systems integrators, suppliers). Accessibility is similar to the concept of *communality* as long as the data access is provided through a common and integrated pool of data (Phang et al., 2015). While different actors have different objective functions, needs, and viewpoints (Lenz et al., 2018), the accessibility characteristic of network technologies enhances the level of integration (Culot et al., 2020; Fatorachian & Kazemi, 2018) - e.g. between product development and manufacturing, between maintenance and quality (Lenz et al., 2018) through performance indicators than span across multiple application domains e.g. Overall Equipment Effectiveness (OEE), Life-Cycle Assessment (LCA) and Life-Cycle Cost (LCC) (Lenz et al., 2018). Having access to all available data creates the opportunity to unveil new patterns that were hidden in the data (Lenz et al., 2018) thereby increasing *generativity* i.e. the creation of new knowledge (Youngjin Yoo et al., 2012). For instance, during the design and engineering of novel products knowing in advance the impact of a certain parameter creates new knowledge and therefore advances the competitiveness of the organization (Lenz et al., 2018). Accessibility also favors *agility* defined in this context as the ability to implement changes in the company in the real-time and to adapt to new events (e.g. a production line breakdown, a change in product requirements) (Schuh et al., 2017). By integrating and make widely available data, network technologies enhance agility by reducing the response time latency for corrective actions, for instance when production problems arise because data is ready for the analysis of root cause and the effectiveness of corrective actions can be easily monitored (Pigni et al., 2016; Schuh et al., 2017). Moreover, by representing a single source of truth the accessibility/commonality characteristic of network technologies increases the *efficiency* (Lenz et al., 2018) as it avoids unnecessary redundancies (e.g. in the duplication of data), increases task performance (e.g. engineering tasks), and prevents the “reinventing the wheel” issue so that the time is not spent on developing knowledge that has already been accumulated. Another organizational implication of accessibility/commonality is the reduction of *equivocality* (i.e. multiple and conflicting interpretations among different actors and employees about activities) since data represent facts and single sources of truth which reduce the equivocality of events. Moving outside the focal enterprise, it is clear how accessibility enhances the level of *coordination* and *collaboration* with supply chain partners (Chatterjee, Segars, & Watson, 2006; Farahani, Meier, & Wilke, 2016), but also new mechanisms of collaborations with system integrators based more on service rather than standard product provision (Kamalaldin et al., 2020). However, accessibility poses also new challenges caused by the increased behavioral uncertainty of partners determined by opportunistic behaviors. For instance, a customer may use opportunistically shared data (e.g. on resource allocation and status, material usage, job scheduling etc.) to understand how its suppliers use their production resources, control them and possibly opt for more efficient supplier at the end of the contract. In this respect, partners should not exhibit a tight control of network technologies because it hinders the generativity potential of the network technologies (Youngjin Yoo et al., 2012).

Network technologies enable synchronous communication between and among digitized devices and enterprise information systems (Fatorachian & Kazemi, 2018). The ***synchronization*** ensures that data in enterprise information systems are always updated and in real-time, thereby increasing opportunities for optimization and automation of the factory (Cui et al., 2020; Porter & Heppelmann, 2015). For instance, the process states of machines can be used for real-time production planning and scheduling tasks (Lenz et al., 2018). Since it would be challenging to perform one-to-one integration (if not impossible) among different business systems, network technologies leverage the data aggregation layer and require only one connection with the platform (Helu et al., 2017). In this vein, new software or applications (e.g. a warehouse management system) can be easily synchronized with digitized devices and other enterprise information systems (Helu et al., 2017). Synchronization facilitates the digital-to-physical transfer capability (i.e. from product design to manufacturing). Accounting for sensors-based data, a 3D digital product model can better delineate product and manufacturing information (Ghobakhloo, 2018; Tao et al., 2018), Drawing on different standards (e.g. STEP, G-Code, MT Connect, QIF) and virtualization technologies (e.g. equipment-embedded sensors or machine vision sensors), the "as-executed" physical product and its "as-inspected" virtual product (e.g. obtained with, can be compared with "as-designed" or "as-planned" 3D digital product model (Anderl, 2015; Helu et al., 2017; Kwon et al., 2020), obtaining an accurate quality inspection of each product component (Moru & Borro, 2020) Table 2 summarizes the properties of network technologies and their organizational implications.

Table 2. Properties of digital technologies

Forms of digital technologies	Properties	Description	Organizational Implications[2]	References
Physical-digital interface technologies (Definition: a collection of mainly hardware technologies to bridge the physical reality of equipment and product components with the cyber-space e.g. sensors, machine vision, RFID, smart labels, augmented/virtual reality) (Related Industry 4.0 concepts: *Digital Twin, Internet of Things*)	Traceability	Ability to identify each object (e.g. equipment or product components), locate, retrieve status (e.g. "in use, in storage, being retrieved") in real-time. This data ("traces") is recorded into "memories" that keep track of the six basic elements of an event (Who, Where, When, What, Why, How) e.g. when a product component was processed?	• Increasing monitoring and control by tracking activity and authenticating objects • The object "traces" can be used for guaranteeing product safety and for troubleshooting quality or equipment issues • The trustworthiness of data provenance and/or parts manufactured	(Anderl, 2015; Balsmeier & Woerter, 2019; Halawa et al., 2019; T. D. Hedberg et al., 2019; Kallinikos et al., 2013; Lasi et al., 2014; Moru & Borro, 2020; Pigni et al., 2016; Youngjin Yoo et al., 2012)
	Virtualization	Ability to represent and simulate faithfully the behaviors of a physical device or a process using sensor-based data (e.g. temperature, humidity, acoustic	• Increase the analyzability of events (e.g. machine breakdown, quality issues) • Operating *within* digital representations • Cognitive overload, increased analytics, "informated" work	(Anderl, 2015; Bailey et al., 2012; Ghobakhloo, 2018; T.

[22] The list of organizational implications provided here is not meant to be exhaustive but to provide some examples related to the topics of the thesis.

		emissions, pressure, speed). It ranges from a simple approach, where only a set of data is gathered and make available in the virtual world, to more complex approaches, where physical objects or processes are simulated to predict their dynamics and behaviors	• Increased joint experimentation and prototyping with customers for effective collaboration through the sharing of context-sensitive data	Hedberg et al., 2016; Lins et al., 2020; Moru & Borro, 2020; Tao et al., 2018)
Network Technologies (Definition: a collection of software, systems, infrastructures, and platforms to integrate vertically and horizontally different streams of data in a unified corporate business system; (Industry 4.0 concepts: *Big Data, Digital Thread*)	Accessibility (Communality)	Ability to provide easy access to a heterogeneous and common pool of data coming from digitized devices and enterprise information systems	• Increased internal integration and working toward common analytical objectives through shared performance indicators (e.g. OEE, LCA, LCC) • Make use of previously unknown mechanisms and knowledge hidden in the data to *generate* new knowledge • Increased agility and efficiency • Reduced *equivocality* of events • Enhanced *coordination* and *collaboration* with supply chain partners • Increased behavioral uncertainty increases the chances of *opportunistic behaviors*	(Farahani et al., 2016; Garcia-Perez-de-Lema, Madrid-Guijarro, & Martin, 2017; Lenz et al., 2018; Phang et al., 2015; Pigni et al., 2016; D. R. Sjödin et al., 2018; Youngjin Yoo et al., 2012)

Synchronization	Ability to establish a bi-directional communication framework between physical devices and enterprise information systems	• Increased automation and optimization of tasks (e.g. production planning and scheduling, design and engineering) by linking machines and enterprise information systems together • A direct link between product design on the one hand and manufacturability and quality inspection on the other hand	(Cui et al., 2020; Helu et al., 2017; Kwon et al., 2020; Lenz et al., 2018; Porter & Heppelmann, 2015; Tao & Zhang, 2017)

Chapter 3

Literature review on management theories

3.1 Introduction

Since digitalization is a pervasive phenomenon that affects organizations at different levels with the potential to transform not only the structure of the whole organization but also its relationship with external partners in the ecosystem this thesis adopts multiple management theories depending on managerial practice investigated. By following the abductive approach of theoretical contextualization in which results and theory are investigated simultaneously (Ketokivi & Mantere, 2010), this chapter reviews the theoretical lenses that will be used in the following chapter. The theories review in this chapter are the Information-Processing View (IPV), the theory of Organizational Sensemaking (OS), the Knowledge-Based View (KBV), and the Transaction Cost Economics (TCE). Depending on the management practices, different theories are used in each of the following chapters (Table 3). Given that these theories have been developed during a different generation of information technologies, which could explain the technological-driven organizational change, this thesis enriches such established theoretical lenses by including the specific traits or properties of digital technologies.

Table 3. Chapter vs management theory

Chapter	Title	Management theory
5	Making Digitalization effective through decision-making practices	• Information-Processing View • Organizational Sensemaking • Knowledge-based View
6	Making Digitalization effective through governance practices with customers	• Transaction Cost Economics
7	Making Digitalization effective through governance practices with	• Knowledge-based View • Transaction Cost Economics

3.2 Information-Processing View

Decision-making has been investigated by different theoretical approaches. A common tenet of all such approaches is that of bounded rationality from the behavioral theory of the firm (Herbert Alexander Simon, 1997). Bounded rationality implies that humans have limited capacity to process information or consciously ignore information which determines sub-optimal decisions (Herbert Alexander Simon, 1997). The bounding capacity for rational decision-making arises from three sources: (i) the individual's limitation in his mental skills, habits, and reflexes, (ii) the extent of information and knowledge possessed, and (iii) values that may diverge from organizational goals (Herbert Alexander Simon, 1997). Starting from the assumption, organizational can increase coordination mechanisms (i.e. goals, hierarchies, rules, and incentives) that delegate decision-making through the hierarchy (von Krogh, 2018). Starting from this, the IPV deals with the second source of bounded rationality i.e. lack and ambiguity[3] of information that translates into task uncertainty. The IPV theorizes the condition under which organizations increasing or decreasing the information processing capacity of organizational members thereby reducing uncertainty (Galbraith, 1974). The IPV sees organizational members as information processors that must deal with task uncertainty and equivocality defined respectively as absence and ambiguity of information (Daft & Lengel, 1986; Galbraith, 1974). Uncertainty and equivocality determine the requirements to process more information for the execution of tasks. In line with the Contingency Theory, the tenet of IPV is to improve decision-making by designing organizational arrangements that exhibit fit between requirements and capacities of information-processing using a variety of organizational practices that either increase the information processing capacity (vertical information systems, group meetings, direct contacts) or reduce the need of information processing (i.e. slack resources, self-contained tasks).

[3] Ambiguity was added in a later theoretical development by Daft and Lengel (1986)

Current digital technologies that generate and collect a large volume and variety of data, and process them with high velocity reduce the cost of information processing and may reduce the need to invest in vertical information systems or lateral relations (Bokrantz, Skoogh, Berlin, Wuest, et al., 2020; von Krogh, 2018). As we will see, this requires a change in decision-making approaches. Using key concepts from the IPV this thesis will examine why a shift from intuition-driven to data-driven is much needed to tackle the opportunities and characteristics of digital technologies and therefore increase organizational performance.

3.3 Theory of Organizational Sensemaking

The static view of IPV has been criticized by the impersonal view (i.e. not socially constructed) of information processing. Organizations not only merely process information but also *interpret* information to achieve a shared interpretation of the environment which is inherently equivocal and uncertain at least at the beginning. When environmental changes, organizational members collect information and put their meaning upon experience and use the ascribed meaning for subsequent understanding and action (Choo, 1996). Stored interpretations are then used to deal with similar past events. In OS terms, decision-making is not only about making choices but also an arena to interpret and make sense of information and only after making choice or deliberating actions (Choo, 1996). Sensemaking allows people to deal with equivocality and uncertainty of the environment by creating rational accounts that enable actions (Maitlis, 2005). Sensemaking both precedes and succeeds choice-making (the output of decision-making): "sense-making provides clear questions and answers" (K. Weick, 1995) that feed decision-making (Maitlis, 2005). Similar to IPV, central to OS is the reduction of equivocality and uncertainty but unlike IPV that aim informs this with organizational practices that enhance the fit between information processing requirement and capacity, OS theorizes under the formation and reformation of social roles and relationships among a group of actors and sense-giving process (K. Weick, 1995). Sensemaking is often associated with critical thinking. People not only process information but also critic, question, argue, contradict, doubt, distrust, etc. (Choo, 1996).

Sensemaking is particularly relevant in the age of digitalization. The sensemaking process can explain why for instance even if data are collected with digital technologies they are not then used in decision-making (Bokrantz, Skoogh, Berlin, Wuest, et al., 2020). With an increasing volume, variety, and velocity of data and improved algorithms, employees increasingly need to make sense of these data which means understanding which problems should or could be addressed (Verganti, Vendraminelli, & Iansiti, 2020). Data are not explicable by themselves; they require human judgment and interpretation to make sense of this data and make a decision. Even when artificial intelligence can effectively search out optimal solutions in a predefined landscape, human decisions remain superior in formulating problems worth solving by humans or machines and in the interpretation of the solutions proposed by algorithms (von Krogh, 2018).

3.4 Knowledge-Based View

The KBV raises similar critics to the IPV: organizations exist not only to process information efficiently to solve problems statically given to organizations but also to create information and knowledge by actively defining both problems and solutions (Nonaka, 1994). This is the premise of the Knowledge-Based View (KBV) of the firm (Grant, 1996). The KBV postulates on the conditions and practices under which organizations absorb external knowledge through search, assimilation, recombination, and application of existing and newly acquired knowledge and the impact of knowledge absorption on organizational performance (Cohen & Levinthal, 1990; Grant, 1996; Savino, Messeni Petruzzelli, & Albino, 2017). KBV argues that a mix of knowledge, both codified and tacit is required to introduce innovation, a key form of knowledge creation (Nonaka, 1994). Explicit or codified knowledge is formal knowledge that is transmitted between individuals and groups. It is often articulated via formulas, rules, procedures, specifications, databases, etc. Tacit or implicit knowledge is a personal knowledge that is difficult to formalize or communicate. It consists of know-how, insights, and intuition arising from experience (Nonaka, 1994). Moreover, because organizations possess a different stock of knowledge, KBV also theorizes that organizations need to integrate specialists' knowledge into the production of goods and services (Grant, 1996). Commonly used practices to access and recombine tacit and explicit and different stock of knowledge are team involvement, personnel rotation, alliance, open-source platforms, university-industry collaborations, search depth, search breadth, etc. (Savino et al., 2017).

The impact of IT on knowledge creation has attracted significant interest in the research community for its ability to enable the search and recombination of knowledge (see Roberts et al., 2012 for a review). However, these studies focus on enterprise information systems, while the implication of "*how digital technologies sustain and change the foundations of organizational learning, absorptive capacity, combinative capabilities, dynamic capabilities or shape open innovation and technological complementarities, remains underexplored*" (Appio, Frattini, Messeni Petruzzelli, & Neirotti, 2018).

3.5 Transaction Cost Economics

The TCE is a general theory of the governance of exchange relationships among organizations (Ketokivi & Mahoney, 2020). The starting point of TCE is that whenever there is an exchange relationship between two parties (e.g. between a buying and a supplying firm) there are *transaction costs* consisting of expenses that occur *ex-ante* such as searching for partners, negotiating cost and writing contracts and *ex-post* such as enforcing contracts, monitoring performance, adjusting to situational conditions, renegotiation and sometimes third-party mediation and arbitration, and in the extreme case litigation (Ketokivi & Mahoney, 2020; Williamson, 1985). Transaction costs, also called *governance costs,* arise from three main transactional factors: asset specificity, uncertainty, and frequency of interactions (Williamson, 1995).

The objective of TCE is to minimize such transaction costs (arising from these sources) by choosing the optimal *governance mechanism* from a supply chain efficiency perspective (Ketokivi & Mahoney, 2020). Literature has largely focused on binary "make" or "buy" decisions, but TCE includes various hybrid governance forms, such as contractual and relational governance mechanisms (Z. Cao & Lumineau, 2015). Contractual governance refers to the extent to which exchange relationship is managed by a contract that specifies the responsibilities and the obligation of each party and includes penalties or safeguards in predefined terms (L. Poppo & Zenger, 2002) that may reduce opportunistic behavior (a driver of behavioral uncertainty) and therefore reduce transaction cost. Contracts are not all equals but they have different "variables" or "dimensions" to manage transaction costs such as duration, completeness, control clauses (flexibility vs rigidity) (Z. Cao & Lumineau, 2015). However, due to bounded rationality and information asymmetry contracts are incomplete, and firms should find different governance practices to manage inter-organizational relationships including *credible commitments* and *safeguards* such as long-term contracts, joint investments, personnel exchange (Halldorsson, Kotzab, Mikkola, & Skjøtt-Larsen, 2007) but also relational-based governance based on reciprocity, mutual understanding, fairness and shared identity (Laura Poppo, Zhou, & Li, 2016). Just as contractual governance is composed of multiple dimensions, the same holds for relational governance. According to Zaheer and Venkatraman (1995), there are *structural* and *process* dimensions of relational governance. Whereas structural dimension refers to the degree of hierarchical or market structuring of the relation, process dimension refers to expected and actual inter-firm activities that accompany the exchange within the framework of governance structure (Zaheer & Venkatraman, 1995). According to this conceptualization, relational governance entails a form of "*quasi-integration*" governance structure indicating a stable, long-term relationship and high dependence of both supplier and customer for business performance while process dimensions entail both relational norms and trust (Artz & Brush, 2000). Whereas *relational norms* refer to expectations about behaviors that are least partially shared by a group of decision-makers and directed toward collective and group goals including elements such as *flexibility, solidarity, information exchange,* and *participation* (Y. Liu, Luo, & Liu, 2009); *trust* refers to confidence in the partner's integrity, credibility, and benevolence in a risky exchange relationship (Z. Cao & Lumineau, 2015). Trust emphasizes the exchange's cooperative atmosphere (Y. Liu et al., 2009). These structural and process dimensions are necessary to ensure that the relationship is continuous, collaborative, and trust-based to increase suppliers' incentive to invest in cost performance improvements (Helper et al., 2014).

A note on transaction and production costs. Transaction costs and production costs are different but related costs. The difference is evident in corporate accounting where the former is treated as overhead costs, while the latter is a direct cost (Ketokivi & Mahoney, 2020). However, transaction costs and production costs are related to two different decisions. First, about governance choice, each party should compare production cost and transaction cost differentials (Ketokivi & Mahoney, 2020). For instance, a firm should consider the production cost savings from market-based transactions over lower transaction costs that an internal organization may face (Williamson, 1985). Second, concerning innovation activity decisions, lower transaction costs provide greater incentives to firms involved in the exchanging relationship to engage in innovation activities including product but also process innovations aimed at reducing production cost. For instance, demand uncertainty determines high transaction costs that force manufacturers to keep excess inventory or excess production capacity which in turn result in higher production costs and thus a lower cost performance. A similar pattern occurs in product development in which technological uncertainty results in both high transaction costs and production costs due to the difference between product design and manufacturability with subsequent delay and reworks. Contractual and relational governance mechanisms may lower transaction costs arising from uncertainty, asset specificity, and infrequent interactions (Dyer, 1997), and in turn provides greater incentive for the firms to engage in cost reduction activities (Blome et al., 2013). The fact that governance mechanisms may reduce both transaction and production costs is documented by Dyer (1997): "The transactor's choice of governance structure influences the incentives of the transactors to engage in value creation behavior for non-contractible such as innovation, quality, and responsiveness" (pp 538). In the automotive industry, suppliers are more willing to bring to new ideas of cost reduction from value analysis and value engineering if the transaction costs are kept low by the governance mechanisms (i.e. contractual and relational) (Dyer, 1997). If suppliers' expectations that cost savings will be jointly shared or even worse that cost savings ideas will be shared with other suppliers for competitive bidding decrease the incentive to invest in cost reduction initiatives. To sum up, the governance mechanisms aimed at reducing the transaction costs between the parties thereby creating incentives for value creation behavior that will ultimately increase cost performance (Dyer, 1997). The point here is that when transaction costs are high (low), the firm's incentive and actual cost performance initiatives will be low (high).

Chapter 4

The empirical research setting: the Automotive Component Industry

4.1 Introduction

The automotive industry is experiencing a period of market turbulence, rapid technological change, regulatory requirements (in terms of safety and sustainability), and dramatic recession due to the coronavirus health emergency. A recent large-scale survey report from 1154 executives of automotive firms report battery, fuel cell electric mobility, and connectivity, and digitalization as the key three megatrends until 2030 (KPMG, 2020). However, COVID-19 may now move the industry's agenda from technology development to survival and operational needs (KPMG, 2020). In this scenario, the adoption of new digital technologies increases the chances of survival of automotive firms (Arcidiacono et al., 2019). There is the need to understand the practical responses in facing the comprehensive challenges of digitalization in the whole automotive supply chain (Lin, Lee, Lau, & Yang, 2018), especially considering the high competition of the automotive industry on technology and functionality of products and related complexity of development (Trautrims, MacCarthy, & Okade, 2017). Since the thesis uses the automotive industry as the setting of the research, this chapter describes the automotive industry, including key actors in the supply chain, the digitalization trends in this industry as well as the discussion of the research method used in this thesis. This chapter can be used to contextualize the other chapters that follow. The chapter is structured as follows. Section 3.2 illustrates the rationale for using the automotive industry as the research setting of this thesis. Section 3.3 provides the industry characteristics highlighting the increasing role of automotive suppliers. A section is dedicated to the Italian automotive industry. Section 3.4 provides the digitalization trends of the automotive supplier industry. The chapter concludes with a discussion of the research method including the description of the quantitative survey, the case studies, and the main quantitative measures used in the thesis related to the adoption of the physical-digital interface and network technologies and the cost performance measure.

4.2 Why the Automotive Industry?

This thesis focuses on manufacturing and specifically on the automotive industry. Manufacturing is often considered as the backbone of the economic system of a country because it is a source of high-wage jobs, industrial and service innovation. It is also a source of attraction of innovative suppliers and experienced talent (Susan Helper, Krueger, & Wial, 2012; Womack et al., 1990). Among manufacturing industries, the automotive industry is regarded as one the most important in terms of GDP and employment. This thesis focuses on the automotive industry for the following reasons.

First, it has a high employment share and accounts for a greater part of the GDP of most advanced countries representing a "strategic sector". For instance, in Italy the automotive industry in its entirety accounts for approximately 258 thousand employees, representing 11,3% of manufacturing, and the annual turnover accounts for 5,9% of Italian GDP (Barazza & Coccimiglio, 2019).

Second, the automotive industry is subject to greater competitive pressure than other industries, which has to deliver complex industrial products subject to high levels of international standards, quality, and efficiency (Liao et al., 2020; Qamar et al., 2018) which determine a continuous need to innovate production process to stay ahead of the competition. Therefore, it is easier that firms in this industry are earlier adopters of new digital technologies (PwC, 2018) and thus to study technology-enabled organizational transformations. Moreover, technologies and managerial practices, that in the automotive industry have been pioneered, are later transferred to other manufacturing industries (e.g. appliance industry). In this respect, the automotive industry has attracted significant interest in the research of inter-organizational relationship due to the changes and the differences of buyer-supplier relationships especially in different countries such as Japan and Western countries and by the fact that inter-firm exchange is ubiquitous (e.g. S. R. Helper & Sako, 1995; Ketokivi & Mahoney, 2020) with outsourcing levels up to 80 percent (Gottge, Menzel, & Forslund, 2020).

This thesis focus on the Italian automotive industry. The choice of a single country has also a methodological advantage. Institutional factors such as country legislation and policies may impact the level of adoption of digital technologies and the approach of firms to digitalization. For example, being in Italy the incentive scheme to adopt strongly linked to financial savings for the adoption of digital technologies, many companies just bought the technologies without considerations of organizational changes. At the same time, no incentives were given, if not later with the introduction of competence center and digital innovation hubs, to organizational redesign and training support. Thus, the same institutional context guarantees that all the surveyed firms have the same level of access to institutional opportunities related to technology adoption and support for organizational design. Similarly, the focus on a single industry set aside exogenous variation due to industry characteristics.

Summarizing, even if a single country and industry studies may often lack generalizability, they have the advantage that the variables studied in this thesis are not dependent on exogenous factors but are endogenous to the firm.

4.3 The automotive industry and the role of suppliers

The automotive industry is characterized by several players (Susan Helper et al., 2019; Womack et al., 1990). The *OEMs* or the *automakers* (such as FCA, Renault, Ford, Toyota) design, assemble, market and finally distribute cars with the help of and *third-party logistic providers* and *distributors*. They preside over a supply chain that includes large *first-tier* suppliers (who directly ship to the OEMs), who are in turn supplied by smaller *second-tier*, who are supplied by *third-tier* suppliers, and so on. The classification is blurry, as second-tier suppliers can also directly serve OEMs. Another classification proposed in Zirpoli and Moretti (2018), group the supply chain players in terms of competence and products. Accordingly, suppliers are divided into *systems integrator* and *providers of modules* (e.g. braking system, powertrain systems, glass modules), *engineering and design* (E&D) firms (e.g. prototypes, engine design, plant layout), *specialized suppliers* that provide components with a high technological level (e.g. dies, stamped products, chassis, engine components, suspensions and transmission component, infotainment, painting) and *sub-suppliers* that produce standard components or they offer a production process (e.g. turning, milling).

From an almost vertically integrated industry, in which price was the main selection criteria for the supply, the industry has gradually moved to high fragmented and specialized industry, in which other supplier selection criteria such as quality, innovation, and technical capabilities have been more considered (Manello & Calabrese, 2019). Now, the industry is characterized by high levels of outsourcing (Gottge et al., 2020). This trend was largely spurred in the global automotive industry by the Japanese model of low vertical integration and supplier integration in just-in-time and lean production from the 1980s' (Schulze, MacDuffie, & A. Täube, 2015), where these practices were already in place (Womack et al., 1990).

OEMs are powerful actors in the automotive supply chain. By developing product architecture, design platforms, and specific models (Schulze et al., 2015), they have the power to determine (or at least set the basis of negotiation) product quality, product development timing, delivery, and costs (Gaddi, 2020). They also have the power to require suppliers to invest in managerial practices related to lean production (e.g. just-in-time, employee involvement, statistical process control, set up time reduction) in which they have already invested in their assembly plants as well as new digital technologies (Gaddi, 2020). Besides, they resist open and industry-wide standards to retain brand distinctiveness and control product design (Schulze et al., 2015).

Nevertheless, the complexity of new product development, driven by technological advancements but also by environmental and safety requirements (Schulze et al., 2015), requires the integration of external partners with specialized knowledge. While OEMs maintain overarching technical knowledge and control of the product architecture (Schulze et al., 2015), suppliers are increasingly obtaining responsibilities in product development which require them to introduce product and process innovations to maintain the relationship. Firms that operate downstream in the supply chain of the automotive industry produce more added-value products and tend to be more specialized than firms operating upstream (Qamar et al., 2018).

This allocation has multiple objectives: to lower the input costs of given products and components due to higher supplier's specialization, to face the general shortage of qualified engineers/operators, to have a clear allocation of responsibility of the product development cycle, in terms of delivery mix and production volume, and to improve the control and responsiveness of a supply chain to guarantee on-time availability, a higher quality of the end-products, and therefore a competitive advantage (Qamar et al., 2018)

Suppliers play an important role in determining the competitiveness of customers, as the cost of purchased material represents more than 50% of the customer's sales (Tang, 1999), and many buyers identify key suppliers as they rely more and more on their performances (Trautrims et al., 2017). Having recognized this, OEMs have gradually shifted from a short-term, adversarial, and contractual relationship with the supply base to more long-term, collaborative, and trust-based governance to increase the suppliers' efforts to improve cost performance (S. Helper & Henderson, 2014).

Another trend that automotive suppliers are facing is globalization (Schulze et al., 2015). Suppliers are being increasingly pressured to increase their productivity from countries with lower labor costs. Sometimes, this type of competition is created by OEMs which put suppliers in high-cost countries to confront those in low-cost countries (Gaddi, 2020).

Such trends are determining increasing pressure for automotive component suppliers to increase cost performance by reducing costs. To do so, several plants are investing in digital technologies. In this respect, the research sample showed that the most pressing challenge for suppliers is related to increase production efficiency.

4.3.1 The Italian automotive component industry

Italy is one of the leading EU countries for the automotive industry, following Germany and France in terms of sales volume. The Italian automotive component industry is composed of a large share of SMEs) accounting for 91% (employment less than 249 employees), while large enterprises (more than 250 employees) accounts for 9% (Barazza & Coccimiglio, 2019). Large enterprises include plants of Multi-National Enterprises (MNEs), established in Italy for the European market but also for research and innovation due to knowledge and technology transfer with Italian universities and research organizations.

Production choices of Italian automotive suppliers have been dependent for the greatest part on FCA, the only OEM with assembly plants in the country, which absorbed 37% of suppliers' sales in 2018 (Barazza & Coccimiglio, 2019). The dependence of the industry on FCA determines that its success is largely determined by the prosperity and investment decisions of FCA in the country. The industry is undergoing a process of transformation characterized by a large drop in the production of vehicles (Gaddi, 2020) (from 1998 to 2018 the number of vehicles produced drop by 1.3) mainly due to the saturation of the European market, which stood at approximately 1 million in 2018 (Barazza & Coccimiglio, 2019). At the same time, there has been increased production of parts and component in the same period. In 1998, 40% of employment was devoted to parts and components. By 2018, this this percentage reached 53% (Gaddi, 2020).

In terms of innovation, suppliers are more focused on introducing process innovations rather than on product innovation (Barazza & Coccimiglio, 2019). This is because product innovation is mainly a prerogative of OEMs especially for core components (e.g. engine) but also a joint contribution of tier 1 and OEMs for peripheral components (e.g. transmission belts). However, if we consider the whole supply chain and the compelling need to reduce cost, it is not a surprise the higher relative and absolute percentage of suppliers that focus on process innovations. Indeed, most tier 2 and tier 3 suppliers do not have a clear product but rather sell machining processes or "machining hours". For them, process innovation is almost the only type of innovation.

The Italian suppliers, especially SMEs, are increasingly competing with central and eastern European countries with a lower labor cost (e.g. Poland, Czechia, Slovakia, Hungary), characterized by state funding and proximity to the German market. To respond to the downsize of domestic vehicle production and the allocation of some assembly plants outside Italy in low-cost countries, suppliers have started to gradually reduce the dependence on FCA (Barazza & Coccimiglio, 2019). To do so, they have started to look beyond country borders to be chained to foreign supply chains, in particular the German and French ones (Barazza & Coccimiglio, 2019; Gaddi, 2020).

4.4 Digitalization trends in the automotive component industry

Digitizing the automotive industry involves mainly three aspects: connected traveler, autonomous driving, and digital factory (World-Economic-Forum, 2016). Connected traveler includes innovations in infotainment, usage-based insurance, and multimodal transportation that are directly addressed to car users. Autonomous driving includes advancements in assisted driving and self-driving. Digital factory, the focus of this thesis, include digital manufacturing and connected supply chains (World-Economic-Forum, 2016).

As far as digitalization of manufacturing or digital manufacturing (hereafter digitalization) is concerned, automotive suppliers are focusing on the process level, which is considered more valuable compared to the product level, especially as factory layouts and production processes are becoming more complex and the output requirements from customers are becoming more complex (Farahani et al., 2016). Focusing on the process level means finding novel ways to increase quality, flexibility, reducing lead times, and eventually reducing product costs. This translates into better access and analysis of production-related data such as breakdown, minor stoppages, tool change, changeover, production speed, and quality data for troubleshooting and predict performance (Arnold, Kiel, & Voigt, 2016) as well as engineering and design, inventory and logistics issues through a better managed end-to-end process, increased transparency and faster response times (World-Economic-Forum, 2016). In this vein, not only production processes are optimized but also automotive suppliers look for better customer relationships with the final and shared objective of cost reduction (Arnold et al., 2016; World-Economic-Forum, 2016).

Automotive suppliers are investing in different functional areas (Farahani et al., 2016). Although several suppliers are active in digitizing the factory, there is a gap between the necessity of promoting Industry 4.0 in theory and the practical response in implementation (Lin et al., 2018).

As far as Italy is concerned, recent evidence shows that Italian component suppliers are very active in the digitalization of the factory, at least compared to other Italian manufacturing industries (MISE, 2017). According to the observatory of the Italian component industry, more than 50% of firms have introduced at least one digital technologies (Cabigiosu, 2019). The most active are specialized suppliers operating in tier 1 and tier 2, followed by systems integrators and providers of modules operating mainly in tier 1. This evidence shows that companies in the upper position of supply chains are more active than firms in lower positions. The same survey shows that more than 1/3 of firms that invest in at least one digital technology have used the fiscal incentives of national plant Industry 4.0 (Cabigiosu, 2019). In a recent qualitative article, Gaddi (2020) showed that Italian suppliers are investing more in physical-digital interface technologies and network technologies (i.e. software and connectivity technologies) than in automation technologies (i.e. robots, additive manufacturing). Specifically, they are making significant investments in connected Manufacturing Execution Systems and Enterprise Resource Planning looking for data integration (Gaddi, 2020). These technologies are being used for the management of all aspects related to (i) planning and scheduling of activities; (ii) monitoring and control; (iii) supply chain coordination and collaboration (Gaddi, 2020).

4.5 The research method: survey and case studies

A comprehensive and multi-respondent survey, with three main sections, was administered respectively to human resource managers, plant managers, and sale managers of Italian automotive supply firms between March 2019 and February 2020. The unit of analysis for this survey is the plant. Before the data collection phase, the questionnaire was pre-tested to ensure accuracy and clarity. The research team, composed of researchers and professors of the Polytechnic University of Turin, sent a draft version of the questionnaire via e-mail to five human resource, plant, and sales managers of five different plants, followed by in-depth interviews with the same informants. Having collected some valuable feedbacks, some questions were slightly modified to increase the accuracy and clarity of the questionnaire.

Starting from a population of approximately 2200 firms, which is updated yearly by the Turin Chambers of Commerce and ANFIA (Barazza & Coccimiglio, 2019), the research team started collecting data from a sub-sample of firms that participate annually in a descriptive survey on the automotive industry, conducted by the aforementioned organizations, and who declared their willingness to participate in our research (approximately 600 firms). Before sending the questionnaire via email, the research team contacted each of the firms by phone to ensure their commitment to the research and to establish the number of plants that could participate in the research. The target firms were then enlarged to involve those included in the database but outside this sub-sample. The sample was stratified considering three main characteristics: (i) the size of the firm; (ii) the position in the supply chain; (iii) the Italian region. During the data collection, the research team ensured that these three variables were representative of the population of Italian automotive suppliers (Table 4).

A total of 102 auto supplier plants participated in the survey. The response rate was 16.8% over the sampling frame and 4.5% over the population. The participants were mainly SMEs (81%) placed in tier 1 (42.6%) and tier 2 (43.2%). Table 4 reports the descriptive characteristics of the sample and population based on the data included in the reference database (Barazza & Coccimiglio, 2019).

Table 4. Sample and population demographics

	Sample		Population	
	N	(%)	N	(%)
Size	102	100	2207	100
SMEs (< 250 employees)	81	81.2	1996	90.4
Large	19	18.8	211	9.5
Supply chain position	101	100	2207	100
Tier1	43	42.6	772	35.0
Tier2	44	43.5	905	41.0
Tier3 or below	14	10.9	530	16.0
Region	102	100	2207	100
Piedmont	46	45.5	752	34.1
Lombardy	18	17.8	598	27.1
Veneto	10	9.9	186	8.4
Emilia-Romagna	6	5.9	221	10.0
Campania	5	4.9	84	3.8
Abruzzo	4	4.0	65	3.0
Lazio	3	3.0	46	2.1
Marche	3	3.0	32	1.5
Other	6	6.0	223	10

To provide a further in-depth investigation of the RQ1, this thesis uses some case studies that were conducted in the same period of the survey in the Piedmont region (north-west of Italy). The selection of case studies was based on (i) different degrees of *product complexity* distinguishing between small and large components, (ii) *position in the value chain* providers of systems and modules (3) *size* of the firm (Table 5). Each semi-structured interview follows a similar protocol. In the first section, the interviewees illustrate the companies regarding customers, products, and investments. After a brief reporting of the research objectives by interviewers, the interviewee was asked to indicate the main digitalization projects, their objectives, and the current challenges. The interview was structured as open as possible leaving the spontaneous emergence of key themes regarding decision-making practices and digital technologies adoption. Upon acceptance by interviewees, each interview was transcribed. Each interview was conducted in the local language (i.e. Italian).

Table 5. Case studies

Case	Interviewee	Interview date	Plant products	Position	Size
Alpha	Plant Manager	03/07/2019	Belts and decoupler	Tier 1	Large
Beta	CEO	05/07/2019	Metal components for braking systems	Tier 2	SMEs
Gamma	CEO	11/07/2019	Small plastic components for car interiors (e.g., doors)	Tier 1	SMEs
Delta	Plant Manager	16/07/2019	Large metal components (e.g., chassis)	Tier 1	Large
Epsilon	Plant Manager	26/07/2019	Keys and locking systems	Tier 1	SMEs
Zeta	Plant Manager	08/11/2019	Metal engine components	Tier 2	SMEs
Eta	Plant Manager	11/11/2019	Microchip	Tier 1	SMEs
Theta	CEO	11/11/2019	Metal and plastic dies and components	Tier 2	SMEs
Iota	CEO	13/11/2019	Thermo-plastic and small metal stamped parts	Tier 2	SMEs
Kappa	CEO	14/11/2019	Metal components	Tier 2	SMEs
Lambda	CEO	15/11/2019	Leaf springs	Tier 3	SMEs
Mu	Production Manager	22/11/2019	Drivetrain system	Tier 1	Large
Nu	CEO, Plant Manager	29/11/2019	Metal Component	Tier 2	SMEs
Xi	CEO	22/01/2020	Stamped metal components	Tier 1	Large

4.5.1. Measures and statistical techniques

To measure the adoption of physical-digital interface technologies, the survey asked the plant managers to indicate whether they adopted or did not adopt a specific technology of this subset. The list of technologies included equipment-embedded sensors, machine vision, tracking technologies for product components, and visualization technologies (e.g. augmented/virtual reality, wearables). To obtain a measure of the adoption of physical-digital interface technologies, the binary variables were summed to obtain a construct that ranged between 0 and 5. To measure the adoption of network technologies, the survey asked whether the plants used an integrated corporate business system that integrated and linked sensor data and enterprise information systems (e.g. MES, ERP, SCM, CRM). To ensure that the network technologies were used effectively, the survey asked the extent of integration. A similar operationalization of technology adoption has been done in Agostini & Nosella (2019) and Tortorella & Fettermann (2017).

The dependent variable, that is, **cost performance**, was measured in terms of **cost reduction** (Blome et al., 2013; Trantopoulos et al., 2017). This variable measures whether a plant was able to reduce the unit production cost over the last three years by more than 3%. Although firms acknowledge intermediate outcomes like machine uptime, improved product quality, safety, information sharing, and inventory management when investing in digitalization, the outcome of efficiency-driven investments ultimately target production cost reductions making this a measure for cost performance also defined in this context as or digital process innovation performance (Trantopoulos et al., 2017). While the original scale of the variable was a Likert Scale ranging from "1" to "5" where "5" represents a cost increase in the last three years, this thesis transforms this variable into a binary variable to isolate the firms that increase cost performance from those that either increase or keep steady the cost performance levels. Since the dependent variable is binary, the appropriate statistical technique is the **logistic regression** (Hair, Black, Babin, Anderson, & Tatham, 2014). Applying an Ordinary Least Squares (OLS) regression or other regression techniques would not be appropriate in this case, because OLS models assume the distribution of the error term follows a normal distribution, which is not the case for binary outcomes. In each logistic regression, a set of control variables that could have an impact on cost performance was included. In order to control for **common method variance** (i.e. variance that is attributable to the measurement method rather than to the constructs the measure represents), the survey relies on two different informants (i.e. the plant manager and the sales manager) who answered two different sets of questions. Moreover, the dependent and independent variables were separated into two different sections, Thus, the common method variance was minimized by obtaining data from different (and independent) sources (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003).

Table 6. Performance and digital technologies adoption measures

Construct	Measure	Operationalization
Cost performance	What has been the average annual percent change in your unit costs for this product over the last year and the last three years? • Decreased < 10% (1) • Decreased 3.1 – 10% (2) • Little Change (+/- 3%) (3) • Increased 3.1 – 9% (4) • Increased > 9.1% (5)	Binary: value 1 if respondent answers (1) or (2), 0 otherwise
Physical-digital interface technologies	Which of the following technologies do you use in this plant today? (0/1) • Sensors installed on equipment to continuously monitor work conditions and process parameters • Machine vision that allows the computer to inspect images used in metrology and other activities of process quality control • Tracking technologies for materials (e.g. RFID, bar codes, QR codes, etc.) to track location and status within the plant for logistic purposes (0.73) • Tracking technologies for products (e.g. RFID, bar codes, QR codes, etc.) to track location and status outside the plant for supply chain purposes (0.63) • Human-Machine interface technologies (e.g. augmented reality, virtual reality, wearables, display touch) (0.58)	Continuous: a sum of three binary variables
Network technologies	How is data on operations (quality, output, etc.) gathered in this plant? (Please check all that apply) (0/1) • "We use a unified corporate business system that integrates sensors data with data from enterprise information systems (e.g. ERP, MES, CRM, PLM)" • "Data remains in siloes; it is hard to link together data from different departments (such as HR, operations, sales)" (*reversed*)	Continuous: a sum of two binary variables

4.6 Challenges ahead and current situation

This chapter concludes with a presentation of the most important challenges faced by automotive suppliers in their plants using the survey data (Figure 3). The respondents (plant managers in this case), who were asked to indicate up to three challenges, reports that the two most pressing challenges are to continuously improve efficiency levels (65% of the plants) and keep quality levels of a product under control (53%). This shows how complex is for manufacturing firms to increase cost performance. The survey data show that only 15.6% of plants were able to reduce product unit costs by at least 3% in the last three years. Apart from performance challenges, the other most important challenge reported is "finding workers with the skills we need" (43%). Introducing advanced production technologies is indicated only by 28% of plants suggesting that the key issue is not on the introduction but rather on how to purposefully use such technologies to increase efficiency levels. Indeed, the adoption of physical-digital interface technologies is widespread as shown in Figure 4. By contrast, the adoption of network technologies is lower as shown in Figure 5.

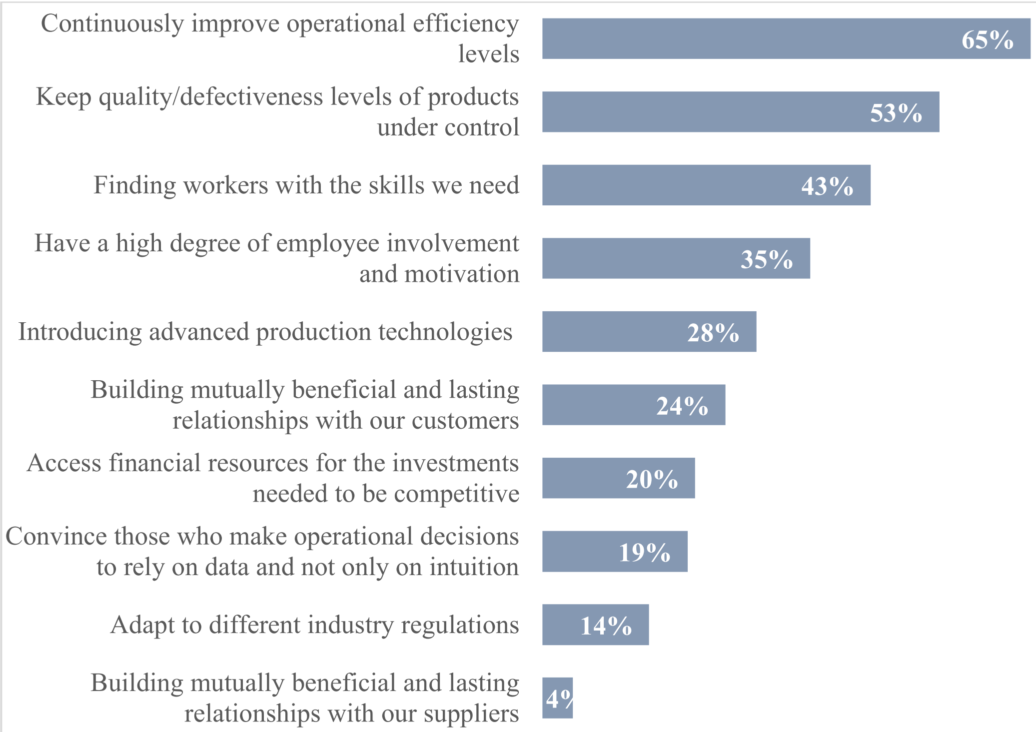

Figure 3. Main challenges faced by the Italian automotive suppliers

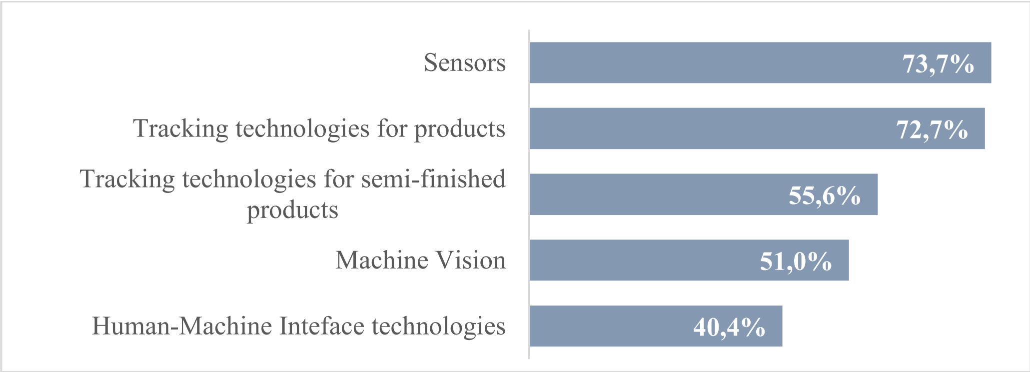

Figure 4. Adoption of physical-digital interface technologies (% of plants)

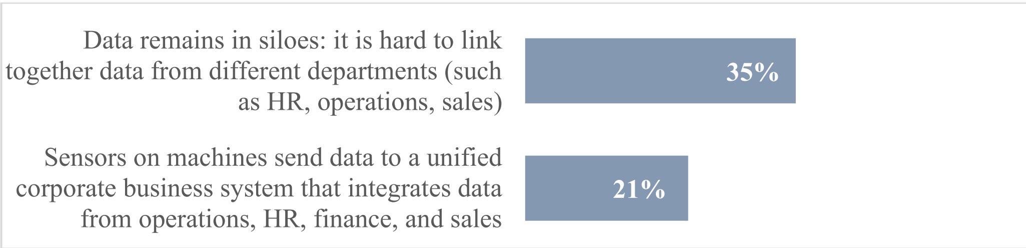

Figure 5. Adoption of network technologies (% of plants)

Crucially, only 19% of plants see the shift from intuition-driven to data-driven as a challenge (Figure 3). There could be two explanations for this: either manufacturing firms have already embarked on and arrived at a transformation of employee's mindsets toward data-driven, or the majority of manufacturing plants have not yet understood the importance of data-driven decision-making. The answer to this question is provided in Figure 6 which points towards the second hypothesis. Figure 6 shows a slight majority of plants (57%) stuck to the intuition-driven decision-making approach.

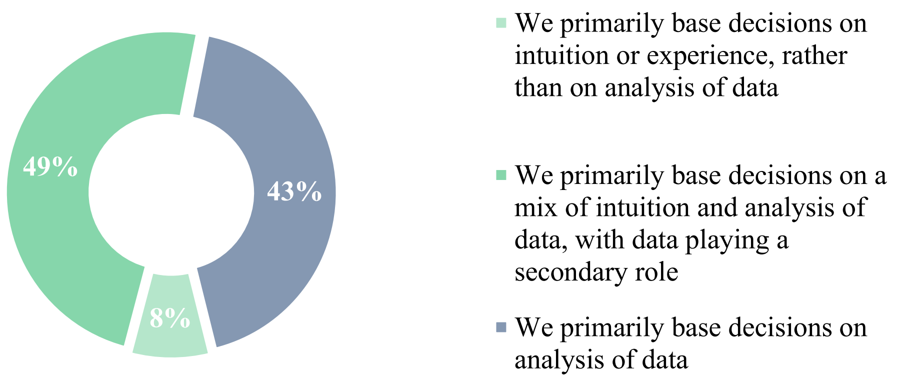

Figure 6. Share of plants by decision-making approach (% of plants)

As far as collaboration with system integrators is concerned, a tiny percentage of plants (4%) declare the "building mutually beneficial and lasting relationship with our suppliers" (Figure 3), suggesting that manufacturing firms are still far from perceiving collaboration with system integrators (key suppliers of digital technologies) as strategic. This is confirmed by the fact that only 3% of companies share data with the system integrators to receive data analytics services despite 44,3% has collaborated with them.

Concerning collaboration with customers, Figure 3 shows that only 24% of firms report the development of a collaborative relationship with customers as a key challenge. This result may suggest that the supplier-customer relationship is to a good extent already based on both relational and contractual governance mechanisms which are effective for supplier performance. However, another explanation of this result points to the fact that companies may have not understood properly the challenges and opportunities of adopting digital technologies in supply chain governance. In this respect, there is high uncertainty about the behavior about customer behavior regarding the sharing of data and information. A key question from the survey asked sales managers the level of collaborative problem-solving with key customers by asking firms to which extent they agree with the following statement: *"We feel that our customer often uses the information we provide to check up on us rather than to solve problems."*. The distribution of the answers is very skewed with no clear patterns. This suggests that plants in the sample have very different perceptions of the behavioral uncertainty of their customers when data and information regarding product and processes are shared with customers which calls for an understanding of the interplay between digital technologies adoption and supply chain governance mechanisms (both relational and contractual).

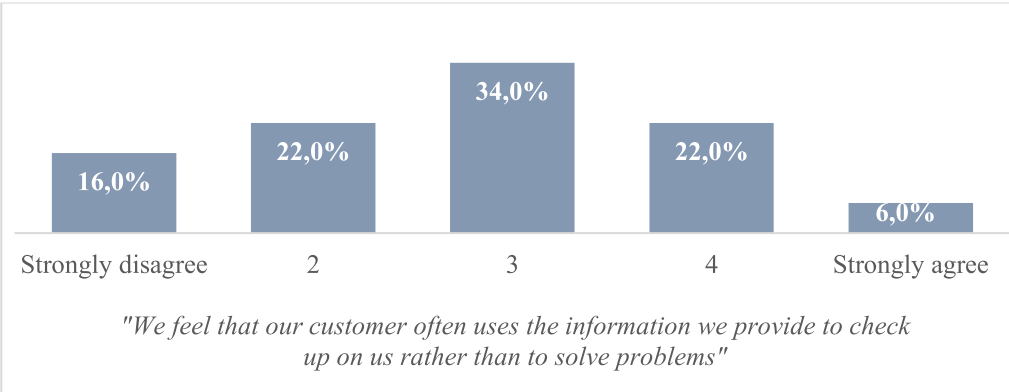

Figure 7. Uncertainty regarding information sharing

Chapter 5

Making digitalization effective through decision-making practices

5.1 Introduction[4]

The Nobel prize Herbert Simon argued that management is essentially organizational decision-making (Herbert A Simon, 1960): all organizational actions are initiated by decisions, and all decisions are commitment to actions. Therefore, a key to understand how data generated by digital technologies create value is to study how it drives decision-making (Bokrantz, Skoogh, Berlin, Wuest, et al., 2020). Two main decision-making approaches can be found in manufacturing firms: the intuition-driven decision-making (experiential, unconscious, and holistic) and data-driven decision-making (Flores-Garcia et al., 2019) (analytical, conscious, and sequential). Some scholars argue that decision-making should be largely based on data analysis which could lead to better outcomes (e.g. E Brynjolfsson et al., 2011; Provost & Fawcett, 2013). Others suggest a more balanced approach where judgment and experience should be considered as well (e.g. Shah et al., 2012; Thiess & Müller, 2018). In the management practice, confusion arises on which is the optimal decision-making approach when adopting digital technologies to achieve efficiency improvements. In this chapter, the two approaches are compared, focusing on a particular subset of decision-making related to cost performance reduction, .e. those "production decisions" (Bloom et al., 2014) taken at an operational level. n this context, decisions are often made in response to events that cause state changes of objects (e.g. machines, orders, product components, customer requirements). Events can range from short-term nature, for example, production line breakdown, missing material, quality issue, to medium- to long-term, for example, a change of product requirements and the associated modifications to the product design itself. The decision-making process involves the analysis of the event that results in actions to provide a countermeasure and eventually prevent the occurrence of the same in the future.

The objective of this chapter is therefore to analyze the different approaches toward digitalization and decision-making, how these are linked to cost performance, and provide managers with concrete actions to make investments in digitalization effective.

[4] The contents of this chapter have been taken from a working paper that is going to be submitted at the California Management Review with the title "To make Manufacturing "Smart", start with Data-Driven Decision Making".

The theory of decision-making is both prolific and heterogeneous. Being the most used in organizational design literature, this chapter uses the IPV, OS, and KBV during the theoretical contextualization approach when iterating between results and explanations for such results. The IPV sees organizational members as information processors that must deal with task uncertainty and equivocality defined respectively as absence and ambiguity of information (Daft & Lengel, 1986; Galbraith, 1974). OS provides a different perspective arguing that employees are not merely processors of data and information but also *interpret* information to achieve a shared interpretation of the environment by putting their meaning upon experience and use the ascribed meaning for subsequent understanding and action (Choo, 1996). The KBV raises similar critics to the IPV: organizations also create information and knowledge by actively defining both problems and solutions (Nonaka, 1994) and by searching and recombining existing and newly acquired, tacit and explicit knowledge (Cohen & Levinthal, 1990; Grant, 1996; Savino et al., 2017).

Using key concepts from IPV, OS, and KBV this thesis will examine why a shift from intuition-driven to data-driven is much needed to tackle the opportunities and characteristics of digital technologies and therefore increase organizational performance.

5.2 Theoretical background and framework development

5.2.1 Decision-making approaches: intuition-driven vs data-driven

Two main types of decision-making approaches can be distinguished, arising from two different types of information processing systems in human beings (Dane & Pratt, 2007): the intuition-driven decision making (experiential, unconscious, and holistic) and data-driven decision making (analytical, conscious, and sequential) (Flores-Garcia et al., 2019). Intuition-driven decision making refers to affectively charged judgments that arise through rapid, non-conscious, and holistic associations (Flores-Garcia et al., 2019), and is associated with having a strong hunch or feeling of what is going to occur; the experiential approaches of decision-makers; the difficulty in explicating the reasons for making a choice; and the prevalence of tacit knowledge in making decisions. On the other hand, data-driven decision-making is associated with having performed an analytical assessment of what is going to occur; the analytical approaches of decision-makers; the easiness in explaining the reasons for making a choice; and the prevalence of explicit knowledge in making decisions. Differently to intuition-driven decision making, data-driven decision making involves quantitative assessment, decomposition and recombination of data and information that arise through slow, conscious and sequential associations (Julmi, 2019) (Table 7).

Table 7. Comparison of decision-making approaches

	Intuition-driven	Data-driven
Speed	Fast	Slow
Deliberation	Non-conscious	Conscious
Associations	Holistic (pattern-based)	Sequential (logic-based)
Information processing approaches	Experiential and emotional	Analytical and rational
Forms of knowledge	Tacit	Explicit

Some studies argue that better decisions occur always as long as they rely on objective data (E Brynjolfsson et al., 2011; Provost & Fawcett, 2013). Other studies set a priority to intuitive decision-making (Dane & Pratt, 2007). Recently, some studies argue that there are no better decision-making approaches but that depends on the structuredness of the underlying event upon which decisions are made (Flores-Garcia et al., 2019; Julmi, 2019). It has been argued that intuition-driven decisions are superior in ill-structured events, characterized by high equivocality and low analyzability, whereas data-driven decision making has a better fit with well-structured events (Flores-Garcia et al., 2019; Julmi, 2019), characterized by low equivocality and high analyzability.

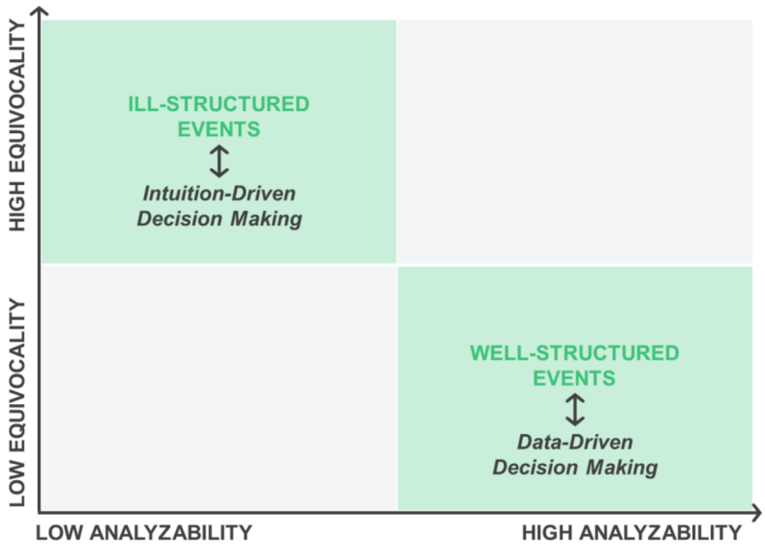

Figure 8. Decision-making approach vs structuredness of an event

The more a decision problem or activity requires the use of computational, objective rules and procedures as opposed to personal judgment and experience (Flores-Garcia et al., 2019), the more it is analyzable. Analyzability can be further decomposed into detectability (the extent to which is possible to capture one or more 5W+H of an event), measurability (the extent to which such 5W+H can be empirically assessed), and interpretability (the extent to which a firm can achieve the needed understanding of the event) (Pigni et al., 2016). Detectability and measurability are linked with data collection methods, interpretability with data processing and analysis. The concept of equivocality – the degree to which there are multiple and conflicting interpretations about an event, and it is associated with problems such as a lack of consensus, understanding, and confusion (Flores-Garcia et al., 2019; Julmi, 2019) – is rooted in the information-processing view of organizations (Daft & Lengel, 1986; Galbraith, 1974). Equivocality is not synonymous with uncertainty (Daft & Lengel, 1986): while uncertainty refers to the absence of information that can be reduced by increasing the volume of data and information (Galbraith, 1974), equivocality refers to the ambiguity of information that can be reduced by exchange subjective interpretations and opinions, form consensus and enact shared understanding uncertainty (Daft & Lengel, 1986). However, current digital technologies (network technologies in particular) are increasingly able to handle not only a great volume of data, but also a variety and a rapid velocity of processing enabling respectively different perspectives and rapid decisions. Apart from exogenous factors, endogenous mechanisms to reduce equivocality and increase analyzability are related to the adoption of different digital technologies with different digital properties (Pigni et al., 2016).

5.2.2 The role of digital technologies in decision-making processes

Today, the emergence of Industry 4.0 represents a potential transformation in the use of data in manufacturing with real-time data captured in digital format from their inception (Pigni et al., 2016). The new generation of digital technologies shaping Industry 4.0 with the new digital properties - of traceability, virtualization, on the one hand, accessibility, and synchronization on the other hand - has assigned once again a central role to data in decision-making (Martínez-Caro et al., 2020).

On the one hand, physical-digital interface technologies can increase analyzability. By virtualizing the physical space and tracking all the activities and processes, they allow to detect, measure, and interpret the 5W+H of an event. For instance, when a disruptive event such as a machine breakdown occurs, sensors and machine vision technologies (part of physical-digital interface technologies) virtualize and keep track of product and process-related data during the manufacturing processes such as workpiece temperature, environmental humidity, noise or acoustic emissions, vibrations, speed, forces, etc. (Lenz et al., 2018). These technologies allow to detect, measure, and interpret why the breakdown occurs and provide suggestions on how to avoid the same in the future. Ill-structured problems (e.g., voice recognition, conversational turns, sentiment analysis, and image analysis) have now been transformed into well-structured problems with the advancements of database and artificial intelligence technologies.

On the other hand, network technologies can reduce equivocality by making accessible and synchronizing data among physical devices and information systems and storing all the data and information in one place. Data that are accessible and common while also real-time thanks to synchronization work a “single source of truth” thereby reducing equivocality of events because workers can have the right information to the right place at the right time. For example, when a recurring event such as production scheduling arise, the real-time data coming from the shopfloor (e.g. machine availability, work-in-process, set-up times, delivery dates, scraps rate, the logic of the product components flow), allow determining the most feasible and optimized production sequence (Romero-Silva & Hernández-López, 2019).

Under these conditions, to exploit the value of digital technologies and increase cost performance, a data-driven decision-making approach widely diffused in the plant seems to be the most suitable one. This chapter asserts that the adoption of physical-digital interface technologies, and their subsequent interconnection through network technologies, can respectively increase the analyzability and reduce the equivocality of events. With this chapter, such hypothesis are tested, for which an increase of cost performance (thanks e.g. to fewer defects, quicker decision making, correcting errors, etc.) cannot be achieved by implementing digital technologies unless a firm is driven by data analysis in its decision-making processes (Figure 9).

Decision-making is not only about making choice but also interpretation. Under conditions where digital technologies generate a large amount and variety of data to find efficiently and effectively solutions to problems arising on the shop floor, the role of employees becomes the one of **sensemaking** that is understanding which problems should or could be addressed (Verganti et al., 2020). Even with artificial intelligence technologies such as machine learning, human beings remain superior in formulating problems either solved by humans or digital technologies (von Krogh, 2018). In this respect, data-driven decision-making includes the activity of sensemaking which occurs collectively and includes the application and recombination of domain knowledge with data and information generated by digital technologies. Employees should now be equipped with critical thinking capabilities that includes the ability to analyze, reason and even question decisions.

Moreover, digital technologies do not allow to find data and information regarding a problem more efficiently increasing information-processing capacity while requiring sensemaking activities, but also to **search and recombine data, information, and knowledge**. Specifically, network technologies allow to development of novel interpretations and knowledge combinations by enabling to search for new and distant information (Lenz et al., 2018).

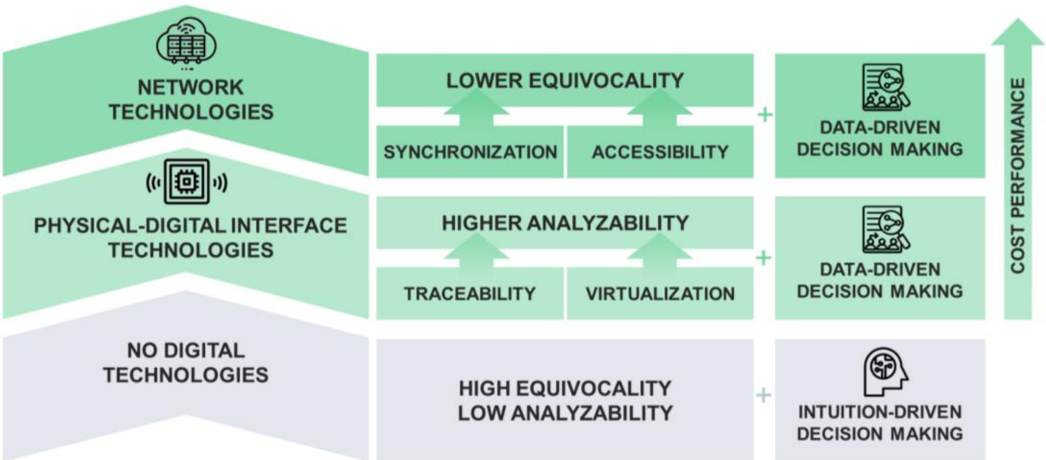

Figure 9. Research framework (I)

5.3 Methodology

The data analysis involved two stages. In the first (quantitative) stage, a set of logistic regressions was performed with cost performance as a dependent variable, and the interaction between the two forms of digital technologies and decision-making approaches. A set of control variables that could have an impact on cost reduction was included such as the size of the plant, percentage of employees with an academic degree, the ratio of R&D expenditure over sales, the presence of variables incentives on salary if a plant is part of a multi-unit firm and the position in the supply chain (e.g. Tier1).

The interaction terms (e.g. physical-digital interface technologies x data-driven decision-making) in the logistic regression allow identifying four patterns of decision-making approaches and technology adoption. Since the logistic regression coefficients provide the coefficient in logarithms of odds (i.e. ratio of the probability of success over the probability of failure), by exponentiating it is possible to determine the odds ratio and then the probability to reduce cost with the simple formula $prob_{cost\ reduction} = \frac{odds}{(1+odds)}$. These coefficients represent the predicted probabilities of occurrence of an event (in this case the achievement of cost reduction by the focal firm) (Hair et al., 2014). To check the presence of these four patterns as well as the actual percentage of firms that reduce cost under different conditions of technology adoption and decision-making approaches, a hierarchical cluster analysis was performed using the complete linkage model excluding those companies that have not adopted any of the physical-digital interface technologies (14% of the sample). Two separate cluster analyses were performed forcing respectively data-driven decision and intuition-driven decision-making equal to 1. In this way, it was assured that there were not mixed clusters in which plants may have different decision-making approaches in the same cluster. The two dendrograms provide support for two clusters solutions which sum up to four clusters (Figure A1 in the Appendix). The tables showing the descriptive statistics of cluster analysis are available in the appendix (Table A2).

The second (qualitative) stage comprised the confirmation of the quantitative results of the prior stages through a qualitative approach using semi-structured interviews with the CEOs and plant managers. Based on the answers to the questionnaire each plant was assigned to a particular cluster. This stage was followed by a review of the qualitative data regarding decision-making approaches and forms of digital technologies adopted to corroborate the quantitative results.

Table 8. Measures for decision-making approaches

Construct	Measure	Scale
Intuition-driven decision-making	How is the data used in this plant? (Please check all that apply) (0/1) • "We primarily base decisions on intuition or experience, rather than on analysis of data" OR "We primarily base decisions on a mix of intuition and analysis of data, with data playing a secondary role"	Binary
Data-driven decision-making	How is the data used in this plant? (Please check all that apply) (0/1) • "We primarily base decisions on the analysis of data"	Binary

5.4 Results

Table 9 shows the results of the logistic regression with the three interaction terms: physical-digital interface technologies, network technologies, and data-driven (intuition-driven) decision-making. The results show that positive and significant effects on cost performance can be found concerning data-driven decision-making even when no technologies are adopted (β=2.015; p<0.1; column 4) and when the three interaction terms are all present (β=2.713 p<0.05; column 4). Notably, when both physical-digital interface and network technologies are adopted but no data-driven decision-making is in place the coefficient is negative and significant (β=-2.383 p<0.05).

Table 9. Results of the logistic regression (I)

Dependent Variable: Cost Performance	(1) Coefficient (Std. Err.)	(2) Coefficient (Std. Err.)	(3) Coefficient (Std. Err.)	(4) Coefficient (Std. Err.)
Physical-Digital Interface Technologies	-0.379	-0.0884	-0.885	-0.930
	(0.426)	(0.545)	(0.857)	(1.058)
Network Technologies	0.240	0.684	-0.755	-1.264
	(0.438)	(0.528)	(0.835)	(0.992)
Physical-Digital Interface Technologies x Network Technologies	0.429	0.330	-1.470	-2.383*
	(0.410)	(0.462)	(0.987)	(1.200)
Data-driven Decision-Making			1.207	2.015+
			(0.961)	(1.108)
Data-driven Decision-Making x Physical-Digital Interface Technologies			0	0

			(.)	(.)
Data-driven Decision-Making x Physical-Digital Interface Technologies			0.506	0.842
			(0.957)	(1.085)
Data-driven Decision-Making x Network Technologies			0	0
			(.)	(.)
Data-driven Decision-Making x Network Technologies			0.995	1.948^{+}
			(0.943)	(1.170)
Data-driven Decision-Making x Physical-Digital Interface Technologies x Network Technologies			1.899^{+}	2.713^{*}
			(1.069)	(1.284)
Size		-0.288		-0.288
		(0.631)		(0.631)
Enterprise Information Systems		-0.00886		-0.00886
		(0.464)		(0.464)
Multi-Unit Plant		-0.00388		-0.00388
		(0.480)		(0.480)
R&D Intensity		0.00438		0.00438
		(0.512)		(0.512)
% of Employees Academic Degrees		0.717		0.717
		(0.498)		(0.498)
Incentives Productivity		-0.754^{+}		-0.754^{+}
		(0.432)		(0.432)
Supply Chain Position		-0.971^{*}		-0.971^{*}
		(0.443)		(0.443)
Constant	-1.445^{**}	-1.449^{**}	-2.652^{**}	-3.464^{**}
	(0.454)	(0.533)	(0.847)	(1.016)
Observations	90	88	90	88
Pseudo R^2	0.157	0.220	0.157	0.220

Note: Coefficients in odds ratio, standard errors in parentheses, $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.0$

Since in this thesis the focus is on the interplay between technology and organizational design the plants that have not adopted any digital technologies have been removed from the following cluster analysis. The results of the cluster analysis (i.e. dendrogram, summary statistics, and Anova) are provided in the appendix (Figure A1 and Table A2). The cluster analysis allows identifying four different profiles of firms by linking the two stages of digital technologies adoption (adoption of physical-digital interface technologies followed by network technologies) and decision-making approaches. For each configuration, the probability of reducing costs from the logistic regression was calculated, and also analyzed which of these configurations has already a realized impact in the plants of the sample by analyzing the share of plants that had reduced cost in the last three years (Table A2, Figure 10).

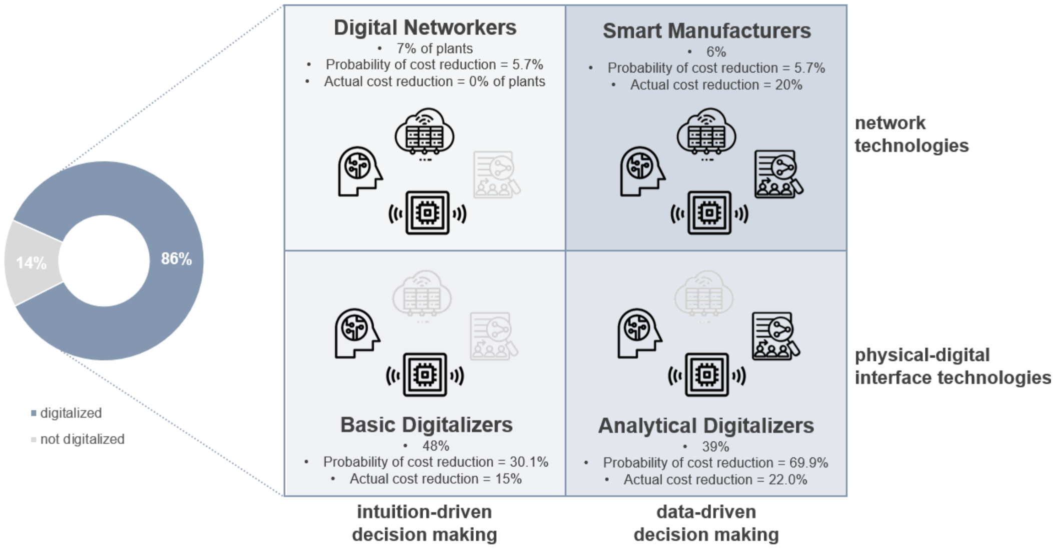

Figure 10. Potential and achieved cost performance by cluster

5.4.1 Different technology and decision-making approaches

Basic Digitalizers. The highest number of plants in the sample (48%) exhibit an intuitive approach to decision-making while adopting physical-digital interface technologies. Despite having a range of historical and real-time data thanks to traceability and virtualization property of physical-digital interface technologies, firms in this cluster ignore such data and continue to make decisions on intuition. In this regard, a plant manager noted: "*We have recently bought machines that speak but we do not listen*".

High equivocality and low analyzability of events are managed by experienced workers that have deep knowledge and expertise in their field results from years of experience. A case in point is a medium-sized firm. In heat treatment processes, some experienced workers have come to realize when the workpiece was ready to be removed by looking several times in their work-life how the materials react based on the color of the workpiece. Being afraid of losing this knowledge once these workers will retire, at the time of the interview, they were trying to standardize such knowledge by empirically annotating the temperature of the workpiece when these workers extract the workpieces from a furnace with a thermocouple. This case illustrates a legacy of intuition-driven decision-making approaches in production plants, but it also reports a tentative to become more scientific. However, this was due to the fear of losing this knowledge once the workers either retire or move to another company, which in turn is determined by a lack of apprentices in the job market once used to exchange tacit knowledge. In this case, the data-driven decision-making approach seems a mean rather than an end. This secondary view on the analytical approaches is found in another plant, where the manager notes that the implicit knowledge of machine tools and dies developers should remain "high" is critical for machine performance, while the analytical component of decision-making in developing tools and dies is used only in second moments of team aggregation. Another mid-sized plant points out that the machines collect lots of data, but they do not have the people able to interpret those data and drive decision-making. The manager reports a skills gap: the workforce with both data analytics skills and domain knowledge in traditional manufacturing domains such as milling, molding, etc. However, unlike other firms in the other clusters, these firms are not considering an upskilling of the current workforce in data analysis skills but prefer waiting (a long time) for industrial policies that will address this need.

The analysis estimates that the probability to reduce unit product cost reaches only 30,1%, while the firms that achieved cost reductions are only 15% in this cluster (Figure 10).

Analytical Digitalizers. The plants in this cluster (39%) have adopted physical-digital interface technologies and base their decisions on the analysis of data. The traceability and virtualization of physical devices (e.g. product components, equipment) allow increasing the analyzability of events by including the collection and analysis of managerial data, as well as sensory data from equipment and product components. However, the loose integration of digitized objects and enterprise information systems creates digital "silos". These plants lack the opportunities of data synchronization and accessibility of network technologies that would reduce the equivocality of events and therefore need more time to deal with specific situations. In these organizations, there is still a relatively high time latency between the occurrence of an event and counter-measure decisions since information systems are not end-to-end integrated. Nevertheless, having invested in the analytical and data-driven approach in decision-making, they are on the right path to make the step toward smart manufacturers. When asked about the most important challenges facing currently in the plant, a plant manager of a small-sized company answers: "*to have a digital data report of the factory, to learn how to manage data and to use them as drivers of operative decisions. We would like to answer questions like: How much does this component cost? How many hours does it take to be produced*?". For these plants, KPIs such as the OEE or scrap rate are only the starting point to go back that is to understand what, where, and why of problems and how to solve them to have cost savings in the future. To become more data-driven and analytical, companies in this cluster, even small- and medium-sized companies, hired young engineers with strong business acumen and data analysis skills or experienced engineers that have worked for several years in large enterprises of the automotive sector. Therefore, they also have a deep functional knowledge of manufacturing processes and continuous improvement practices. For other employees (line or middle line employees), these firms do not wait for the external training system to provide workers with both domain knowledge and data analysis skills, but initiated proactively a training path to increase analytical skills of their workers: "*before, the employees did not know how to read a drawing, now there is the drawing, the list of steps to follow during the manufacturing process, the classification of a defect in which is required to assign the right defect cause*". The majority of firms in this cluster report lean management practices as enablers of analytical and data-driven approaches to decision-making. One plant manager noted: "*The lean approach has taught us how to measure ourselves*". Indeed, lean production is essentially a rational and scientific approach to decision-making (Spear & Bowen, 1999). When the plant learns how to measure business processes, then the most important step is analyzing and interpreting the data to identify improvement opportunities. The same plant manager noted that workforce must now have more than ever a critical thinking capability - that is the ability to analyze, reason, and question decisions - as data could be wrong, and one must understand in the immediate if that data is an error or it is a process drift.

The logistic regression analysis estimates that the probability to reduce unit product cost reaches 69.9%, the second-highest value. At the moment, 22% of the firms in this cluster already achieved cost reductions (Figure 10).

Digital Networkers. The plants in this cluster (7%) have adopted both physical-digital interface technologies and network technologies. The traceability and virtualization properties along with synchronization and accessibility allow the creation of a plant digital twin in which information systems have sensory data and employees can access a common pool of data. However, despite the investments in digitizing and integrating data workers ignore these data during the decision-making process by relying on intuition and experience. As far as high equivocality and low analyzability events are considered, these firms do not exploit the digital infrastructure but tend to use intuition-driven decision-making approaches. In plants belonging to this cluster this "low fit" between the decision-making approach and type of digital technologies adopted can be a problem and even a source of higher equivocality with some workers not knowing what the best approach is to solve problems. The digital initiatives and the data-driven approach promoted by management and a little number of workers clash with the large base of intuition-driven culture especially present on the shop floor. A plant manager noted that since the network technologies are designed to work already efficiently, the people should adapt to the technology and not vice versa. This low fit is reflected in performance. Our analysis estimates that the probability to reduce unit product cost reaches only 5.7%, the lowest compared to the other clusters. None of the firms in this cluster achieved cost reductions

Smart Manufacturers. The lowest number of plants in our sample (6%) exhibit a data-driven approach to decision-making while adopting both physical-digital interface technologies and network technologies. Firms in this cluster reduce equivocality of events with the accessibility and synchronization properties of network technologies and increase analyzability with the virtualization and traceability properties of physical-digital interface technologies. Firms in these clusters have a data-driven approach to decision-making just like the Analytical Digitalizers, but they are facing a more advanced stage of technology adoption that allows them to reduce the equivocality of events. Informants agree that the expansion of information flows allows to reduce conflicts among functions and work toward cross-domain KPI across departments such as OEE and Lifecycle Costs. Having the same data accessible enables agreements and reduction of conflicts across functions. In these companies, data increases objectivism and increases common understanding of problems. Consensus on data enables consensus on decisions that is the approval by subordinates and other stakeholders responsible for the successful implementation of the decision. The synchronization property ensures that data and information in enterprise information systems are always updated and in real-time therefore reducing equivocal interpretations. A plant manager noted that network technologies have allowed managing centrally all the production activities while also detecting what is happening at a micro-level. The synchronization allows a rapidity of change over which determine an increase of automation and optimization of tasks (e.g. production planning and scheduling, design and engineering) by linking machines and enterprise information systems together. These organizations can handle faster unforeseen events (e.g. a machine breakdown, deviation of product quality, engineering change requests, etc.) and make faster and better decisions to provide an appropriate response to events.

The logistic regression analysis estimates that the probability to reduce unit product cost reaches 93.8%, the greatest compared to other clusters. As of today, 20% of plants in this cluster have realized such potential of unit product cost reduction.

5.5 Discussion and Conclusion

We often hear from the press that data, a key characteristic of the digitalization phenomenon, is the new oil. Across all industries, experts, and well-known newspapers such as The Economist and Forbes agree that data is an increasingly valuable resource (Economist, 2017; Gilbert, 2017). However, data by themselves will not solve business problems. This chapter highlights that, alongside digital-driven generated data through the properties of digital technologies, a decision-making approach toward data analysis is a required management practice.

From the quantitative and qualitative analysis of survey and case studies data, this chapter demonstrates how making decisions on the analysis of data is one of the value-creating organizational practices needed to exploit digital technologies by improving cost performance (Martínez-Caro et al., 2020). As far as investment in digital technologies is economically feasible, thanks to these incentives, the key issue is not on the adoption of digital technologies *per se*, but how to purposefully use such technologies to increase business value by enabling cost reduction, productivity gains, or revenue increases (Björkdahl, 2020; Martínez-Caro et al., 2020). Forward-looking managers should not think economically on how to substitute old equipment or exploiting the financial advantages of national plans, but on how such technologies once implemented will support value-creating organizational practices such as facilitating decision-making, generating new knowledge, improving customer services, improve coordination and collaboration with suppliers (Martínez-Caro et al., 2020).

It took almost ten years since the term “Smart Manufacturing” was coined, but only now we are seeing the first results of firms that not only digitalized their operations but started also to make decisions based on data and connected their digital twins, achieving cost performance at the plant level. Such digital transformation paths, however, pose several challenges to managers: formalize a data-driven vision, increase a diffuse understanding of operational data, ensure clarity of the related data flows, and achieve agility in the organization. Technological change takes a long time. On the other hand, embarking on organizational and managerial shifts toward a data-driven philosophy can take even longer, but the game is worth the candle.

Theoretical contributions. This section contributes to the literature on decision-making approaches (Flores-Garcia et al., 2019) and data-driven decision-making (e.g. E Brynjolfsson et al., 2011; Provost & Fawcett, 2013). The first contribution lies in the identification of the value of the data-driven decision-making approach when adopting a new generation of digital technologies. Furthermore, it shows that the heterogeneity in the characteristics of digital technologies exhorts a different impact on the conditions (i.e. analyzability and equivocality) under which data-driven decision-making is a superior decision-making approach over intuition-driven decision-making. This chapter contributes to both literature streams by describing the properties of a new generation of digital technologies discussing why and how (i.e. analyzability and equivocality) these technologies requires and enables a data-driven decision-making approach widely diffused inside an organization in order to make digitalization effective.

This chapter also contributes to this literature illustrating the different patterns that companies may pursue toward digitalization to become truly "Smart Manufacturers". Combining the types of digital technologies and decision-making approaches, this chapter found different combinations of technology and organization variables. This chapter also provided the "suggested paths" in terms of pursuing organizational change before or parallel to technological change. When there is a large misalignment between technology and organization (as for the quadrant featuring the adoption of network technologies and an intuition-driven decision-making approach) is a higher challenge for managers to bring back the organization "on track" with technology and organization fit.

Chapter 6

Making digitalization effective through supply chain governance practices

6.1 Introduction[5]

Research has shown that the governance of inter-organizational relationships has a beneficial effect on the performances of supply chains (Dyer, 1996; Roehrich et al., 2020). Different mechanisms adopted to develop and manage buyer-supplier relationships in the supply chain context have been judged essential for the stability of such a relationship and the fulfillment of joint objectives (Z. Cao & Lumineau, 2015; Y. Liu et al., 2009), especially in terms of product costs. Moreover, the exchange of activities between suppliers and customers may favor innovation and collaborative actions(Um & Oh, 2020). The governance mechanisms of the buyer-supplier interaction have been demonstrated to improve cost performances, especially when the complexity of the processes of designing, manufacturing, and delivering within the dyadic relationship is high (Gimenez, van der Vaart, & van Donk, 2012), and when they have a substantial impact on the suppliers' performances (Jean et al., 2020). It is also clearly recognized that both suppliers' investments in specific assets to increase productivity, and a regime of long-term relationships based on trust and reputation, prevent an increase in the cost of governance (Dyer, 1997). Indeed, cost efficiency is enhanced by the exploitation of technological assets, but also thanks to the mechanisms by which the supply chain is managed and governed (Büyüközkan & Göçer, 2018)

Suppliers play an important role in determining the competitiveness of customers, as the cost of purchased material represents more than 50% of the customer's sales (Tang, 1999), and many buyers identify key suppliers as they rely more and more on their performances (Trautrims et al., 2017). This is particularly true in the automotive industry, which represents one of the largest and most dynamic manufacturing supply chains, that has to deliver complex industrial products subject to high levels of international standards, quality, and efficiency

[5] The contents of this chapter have been taken from a submitted paper to the Special Issue of the International Journal of Operations and Production Management "Supply Chain Governance in the Age of Digital Transformation" with the title "The interplay between Digital Transformation and governance mechanisms in supply chains: evidence from the Italian automotive industry"

(Liao et al., 2020; Qamar et al., 2018). The performance of suppliers is fundamental for the success of the overall supply chain, as carmakers are increasingly allocating external spending, assigning responsibilities, and transferring value-adding activities to suppliers, especially in product co-development (Trautrims et al., 2017).

Considering the trade-offs necessary to manage such performances, the role of technology is to offer new solutions that can improve the overall efficiency. The on-going digitalization of manufacturing processes is now driving the change of the entire automotive value chain, intending to increase efficiency and cost savings, as well as enabling business model innovations. Being historically at the cutting edge of innovative organizational and production techniques, carmakers are refocusing their competences on product innovation dynamics to face the compelling trends of global transportation, and, at the same time, they are progressively changing the management of inter-organizational relationships, thereby increasing their complexity (Sutherland, 2005). They tend to shift from a short-term, adversarial, and contractual relationship with the supply base to more long-term, collaborative, and trust-based governance to increase the suppliers' efforts to improve cost performance (S. Helper & Henderson, 2014).

Both large and small-medium sized suppliers are evaluating the adoption of digital technologies at a process level, and prioritizing practices and capabilities to develop the concepts of the so-called "extended enterprise" (Qamar et al., 2018; Sutherland, 2005) intending to achieve a higher level of flexibility and autonomy to best fulfill the customers' requirements (Liao et al., 2020). These technologies enable manufacturers to design and produce both collaboratively and virtually (Brun et al., 2019) and lead to an easier sharing of production data (Büyüközkan & Göçer, 2018). Moreover, a key concern of car manufacturers is the necessity of having increased visibility of the material, components, and finished products, but also of the processes, resources, and capabilities (Farahani et al., 2016). Within this background, the existing literature mainly discusses the digitalization of the automotive industry from the product innovation viewpoint, due to the introduction of data-driven business models and servitisation to fulfill the customers' needs more effectively (Kushwaha & Sharma, 2016; Rachinger, Rauter, Müller, Vorraber, & Schirgi, 2019). Digital innovation at the process level has been mainly studied in terms of process integration, as a result of the higher automation and the use of Artificial Intelligence for better demand forecasting (Liao et al., 2020). Moreover, there is a paucity of studies that consider the suppliers' perspective (Jean et al., 2020), and their involvement in more complex forms of relationships. Such a perspective, which includes a large number of small-sized suppliers, is fundamental, as automotive OEMs and Tier 1 companies often assign the flexibility constraints imposed by current trends in automotive at the expense of their upstream suppliers (Qamar et al., 2018). An understanding of the factors that enhance supplier's performance, such as the adoption of digital technologies, could also help buyers and Original Equipment Manufacturers (OEMs) to establish appropriate governance of the relationship with the supplier that is beneficial for its performance (Liao et al., 2020).

Three research gaps have emerged and they constitute the focus of this chapter:

1) supply chain governance studies tend to focus on the customers' perspective, and mainly concern product innovation (e.g Blome et al., 2013). This chapter focus on the effect of supply chain governance on suppliers' cost performance, as this is a fundamental aspect for supply chain efficiency and a much less researched topic (Jean et al., 2020);
2) a detailed understanding of digitalization in suppliers and its implications on inter-organizational relationships. This aspect has mainly been treated concerning enterprise information systems (Jean et al., 2020; Zhang, 2019), while recent technological advancements in the context of the digitalization of manufacturing processes have not been explored in depth in supply chains (Fatorachian & Kazemi, 2020);
3) in addition to the second point, there is also a need to understand how firms use the different types of technologies that are part of digitalization to obtain a comparative advantage in the supply chain (Lin et al., 2018), especially considering the high level of rivalry in the automotive industry (Trautrims et al., 2017).

Considering the relevance of such questions, this chapter aims to investigate whether the technology adoption that characterizes the digitalization phenomenon offers new ways of shaping governance mechanisms in the automotive supply chain. In particular, this chapter explored the interplay between the ways automotive suppliers adopt digital technologies at a process level to ensure better visibility and interaction with OEMs and other Tier-x customers and their different impact on the effectiveness of supply chain governance mechanisms on the cost performances of suppliers. Building on the TCE theory, as well as on the literature on supply chain governance and the digitalization of supply chains, results show that supply chain actors require investments in digital technologies that are idiosyncratic, in terms of software and data sharing/integration, and require the development of domain-specific technical knowledge and inter-organizational routines. At the same time, they reduce the number of hardware investments and information asymmetries and make more complex governance forms available at a lower cost. These ensure their production is compliant with more compelling design requirements, reduces the cost of controls, increases trust, and establishes new forms of relationship with carmakers (or global Tier 1 suppliers).

6.2 Theoretical background

It is well-known that IT adoption can reduce the costs of communication as it improves the quality and speed of information processing and decision-making, as well as the monitoring capabilities and performance evaluation schemes (Gurbaxani & Whang, 1991). Nowadays, the emergence of new ICT-based technologies, which drive digitalization, is varying the frequency of exchange between customers and suppliers (Brun et al., 2019). The more complex information flows that are generated are also leading to changes in the mechanisms which regulate and support the buyer-supplier relationships (Kamalaldin et al., 2020).

IT has contributed to synergistic activities, such as product co-development, which were previously too expensive to performed jointly, by increasing the degree of vertical integration and the scope of firm activities (Gurbaxani & Whang, 1991). The objective is to share more design activities and manage product development complexity (J. Lee & Berente, 2012) by exploiting the possibility of finding better technological solutions for production efficiency, without increasing the costs related to governance mechanisms.

Several studies have demonstrated the positive effects of the adoption of IT on supply chain integration, coordination, and collaboration (Chatterjee et al., 2006; Jean et al., 2020; Zhang, 2019). Coordination and integration entail the synchronization of supply chain processes and requires the exchange of such information as inventory levels, manufacturing capacity, production volume, order status, and equipment availability (Chatterjee et al., 2006). Collaboration entails the exchange of information and knowledge to develop new or enhanced products/services (Chatterjee et al., 2006). The impact of digitalization on supply chain governance is closely connected to the collaborative sharing of information between partners, which is necessary to achieve improved visibility and transparency (Fatorachian & Kazemi, 2020). Having all the relevant information easily available is becoming pivotal to facilitating the relevant parties in collaborating and making timely decisions based on updated information (Farahani (Farahani et al., 2016). It is suggested that digital technologies thanks to the sharing of product data and traceability can support the development of trust among partners (T. D. Hedberg et al., 2019), which in turn increases their eagerness to exchange, and can therefore enhance supply chain performance (Um and Oh, 2020). By contrast, Jean et al., (2020) have shown that the collaborative exchange of information, enhanced by the exploitation of specific information systems, enhance the effect of formal contracting on supply chain performance, even though they found no evidence for relational governance. Brun et al., (2019) argued that the adoption of digital technologies may affect all the stages of the value chain, as it reduces transaction costs for both internal and external business operations, and efficiency gains allow higher levels of efficiency and competitiveness to be achieved. Higher transparency is also ensured by the increased data gathering and analytics, which reduce the number of potential defects and accelerate the whole process of component design, manufacturing, and delivery (World-Economic-Forum, 2016). Apart from these studies, there is a paucity of studies that analyze the joint impact of digital technologies and governance mechanisms on relationship performance measured from the perspective of the suppliers. This chapter aims at filling this gap.

The forms of digital technologies considered in the digitalization of the automotive supply chain (i.e. physical-digital interface technologies and network technologies), and specifically from the suppliers' perspective, can have an impact on the characteristics of the transactions in the product development and production processes. Enhanced virtualization and traceability reduce the level of uncertainty and the related costs, by guaranteeing a wider (and virtualized) availability of the dynamics, behavior, modeling, and operational data (Tao et al., 2018), and better accessibility to issues on products that are shared through software platforms. Physical-digital and network technologies both represent similar, internet-based solutions for the communication and exchange of information for suppliers, and they hence lower asset specificity investments (Gottge et al., 2020). Finally, costs related to the frequency of transactions, in terms of the number of times actors carry out specific transactions (Williamson, 1985), are lowered by the automation and real-time acquisition and synchronization of data through digital-physical interface technologies, which require less human involvement (Gottge et al., 2020).

However, research has shown that transaction costs are not dependent only on asset specificity, uncertainty, and frequency but on the governance mechanisms in place between the supplier and the customers (Dyer, 1997). Hence, in the hypothesis development, this chapter will focus on the compound impact of the above mentioned technological subsets and relational governance mechanisms on the supplier's effort to increase cost performance considering the higher transparency and traceability of the information flows between customers and suppliers they can provide, especially in shared platforms (Gottge et al., 2020; Helu et al., 2017). This chapter investigates under what conditions the forms of digital technologies could have a positive and differentiated impact on the efficiency of governance mechanisms along the supply chain, and in particular on the cost performance of suppliers. Specifically, this chapter analyzes study the interplay between the mechanisms of contractual and relational governance and the features of 1) virtualization and traceability, enabled by physical-digital interface technologies, and 2) synchronization and accessibility, ensured by network technologies. The complex supply chain environment requires a contingent perspective on the effectiveness of the relationship between buyer and supplier (Huang et al., 2020), in terms of both the duration of formal agreements and the higher integration opportunities offered by the adoption of network technologies. Indeed, buyers can develop and cultivate both strong (and long-term) partnerships and consciously lose (with short-term agreements) relationships in the supply network, according to the diverse characteristics that have to be addressed in the sourcing strategy (Kim, Choi, Yan, & Dooley, 2011; Trautrims et al., 2017). Figure 11 anticipates the research framework, with the developed hypotheses as in the following.

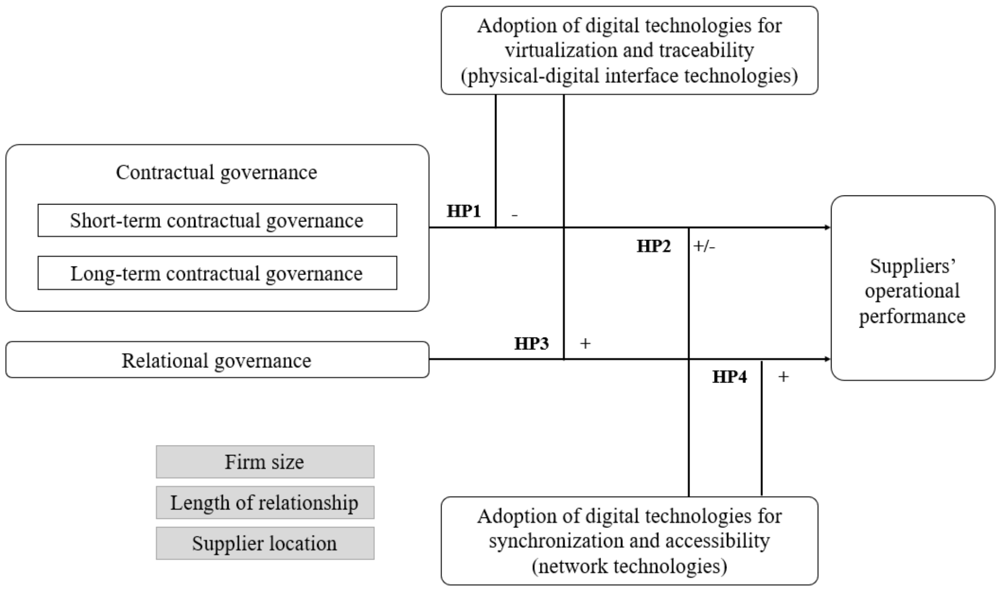

Figure 11. Research framework (II)

6.3 Hypothesis development

Carmakers are increasingly demanding sophisticated and specific component modules from their suppliers, which has led to profound changes in the OEM-supplier relationship (Sutherland, 2005). Suppliers are expected to consolidate greater R&D capabilities and best practices, and to undertake product development activities: carmakers identify and select the most innovative suppliers, especially for strategically important supply categories, but also those that can guarantee larger volumes (Sutherland, 2005; Trautrims et al., 2017). Once they have identified the suppliers that have accomplished competitive sourcing strategies, car manufacturers need to engage in appropriate negotiations and to put in place the contractual governance mechanisms needed to create binding formal agreements that specify the obligations and roles of the partners (Trautrims et al., 2017). Agreements also set conditions about the reliability and capability of suppliers to fulfill given requirements, such as quality, quantity, delivery dates, and price (Johnston, McCutcheon, Stuart, & Kerwood, 2004). On the performance side, suppliers are continuously obliged to balance the trade-off between the efficiency of operations and innovative capabilities to meet the customer's requirements (Liao et al., 2020). Suppliers, to have the right incentive to invest in physical-digital technologies and introduce production improvements, need guarantees that the relationship between the two parties will last for some years and that the customer will not use the "virtualized objects" as a means of control instead of collaboration purposes (e.g. for the refinement of design and models through data capturing by choosing another supplier, rather than using them for collaborative problem-solving) (Anderl, 2015; Chatterjee et al., 2006; Tao et al., 2018). In this case, contracts become less effective in providing incentives for suppliers to achieve cost reductions because the monitoring and control policies of contracts (both short-term and long-term) can now be substituted by a large amount of data and availability of virtual objects, thanks to physical-digital interface technologies.

On the other hand, suppliers could feel more empowered in terms of autonomy, and therefore in terms of the self-determination of their activities in the supply chain and their choices to manufacture and deliver products to buyers (Liao et al., 2020). The features of virtualization and traceability establish a quasi-integration mechanism form (Kim et al., 2011) that prevents opportunistic behavior and thus reduces reliance on both short-term and long-term contracts pertaining to the cost performance of suppliers.

The length of the relationship, the complexity of the transaction, and its governance create different forms of bilateral dependence, where technologies enact alternative mechanisms (with the rationale that more sophisticated and integrated technologies are connected to more complex forms of governance).

Based on the above reasoning, the following hypothesis are proposed:

HP1. *The interaction between contractual governance and the adoption of technologies for virtualization and traceability is negatively related to the cost performance of suppliers.*

HP1a. *The interaction between short-term contractual governance and the adoption of technologies for virtualization and traceability is negatively related to the cost performance of suppliers.*

HP1b. *The interaction between long-term contractual governance and the adoption of technologies for virtualization and traceability is negatively related to the cost performance of suppliers.*

Having data available on traced and retrieved physical objects determines the possibility of controlling and bargaining with the customer. A carmaker or a powerful tier 1 supplier can check opportunities with more competitive suppliers in the use of production resources at the end of the contract (and at the crucial time of switching from one vehicle model to another), especially when these are short-term contracts (Aláez-Aller & Longás-García, 2010). Indeed, network technologies offer opportunities to simplify control procedures and monitory compliance with contracts, and cost savings can be achieved using a continuous exchange of information, but at the cost of greater integration of information collected on the status of production activities (and deliveries), and data about product quality. Customers can leverage these data to monitor but not to improve the cost performance of their suppliers (Liao et al., 2020), especially if there is a short-term contract. The real-time transparency of product-related information and the integration of process-related information promotes superior coordination and collaboration (Fatorachian & Kazemi, 2020), while it can also increase opportunistic behavior by means of the control of the customer. Carmakers usually maintain their contracts with suppliers for the lifetime of a given model (Aláez-Aller & Longás-García, 2010). Contracts with a longer time horizon than the product life cycle can reveal the willingness of organizations to reach the full potential of coordination and collaboration with their partners, and then learn more about how they can work together to accomplish supply chain objectives (Huang et al., 2020). It also represents a form of commitment that the customers will continue the relationship in the long term, thereby avoiding a switch in the supply base. In this way, the suppliers feel empowered in terms of demonstrating their internal capabilities to develop and deliver products aligned with the quality and design requirements of the customers (Liao et al., 2020), also thanks to the enhanced synchronization and accessibility. The duration of formal agreements can reveal the buyer's need to maintain its bargaining power, but long-term partnerships are often characterized by co-operation, an exchange of information, and mutual trust (Aláez-Aller & Longás-García, 2010). The higher level of network technologies and the related transfer of knowledge can be beneficial for the supplier's performance, provided that the buyer and supplier have interacted long enough (Kotabe, Martin, & Domoto, 2003).

Based on the above reasoning, the following hypothesis are proposed:

HP2. *The interaction between contractual governance and the adoption of technologies for synchronization and accessibility is positively related to the cost performance of suppliers*.

HP2a. *The interaction between short-term contractual governance and the adoption of technologies for synchronization and accessibility is negatively related to the cost performance of suppliers*.

HP2b. *The interaction between long-term contractual governance and the adoption of technologies for synchronization and accessibility is positively related to the cost performance of suppliers.*

Considered that car manufacturers are generally eager to involve suppliers in product development, as long as they contribute to the design and innovation processes (Huang et al., 2020), trust (and a consequent collaboration) is especially important for the sharing of production and process data. Physical-digital interface technologies provide real-time information transparency of product-related information, such as information about product development testing, the equipment parameters used during the manufacturing process, the product manufacturing history, and product quality (Tao et al., 2018). In this sense, such technologies can be pivotal in different stages of buyer-supplier cooperation. During the product development stages, physical-digital technologies allow suppliers to collect and share data on product development in real-time, with the aim of tracking materials and detecting errors to authenticate products, and this, in turn, has a positive effect on the production coordination costs (Farahani et al., 2016; Kallinikos et al., 2013; Youngjin Yoo et al., 2012). At the same time, "Digital Product Memories" identify the quantitative parameters (i.e. the most relevant "design requirements") and their change in status that must be controlled during the manufacturing activities (Anderl, 2015; Chatterjee et al., 2006), so that any physical product exactly reflects the official product specifications that resulted in the initial awarding of that supply contract (Aláez-Aller & Longás-García, 2010). If the product is out of specification, real-time information transparency can pinpoint the production problems and immediately drive process improvements at the supplier's site. This type of transparency increases the quality assurance of suppliers' products and makes it easier to introduce relational governance forms, thus creating a new basis for trust-based supply chain relations and joint problem-solving activities. Mutual trust plays a more important role in building supplier empowerment (Liao et al., 2020), and enhances its competitive capability (Huang (Huang et al., 2020), even in terms of production costs. These conditions minimize the costs associated with the governance of the relations and make highly specific investments in knowledge-intensive activities possible and effective.

As carmakers are focused more on product architecture innovations and the responsibility of product integrity (Schulze et al., 2015), their decision to assign the complete development of new components to a supplier can be further legitimated through the use of physical-digital interface technologies that provide a high level of trust, the expectation of joint problem-solving and incentives for open communication. The higher autonomy and control over internal processes enhanced by such technologies lead the suppliers to be more likely to behave proactively, to improve processes continuously, to take risks, and to seek novel ways to solve customers' problems (Vilko, Rumpu, & Koivuniemi, 2012).

Based on the above reasoning, the following hypothesis is proposed:

HP3. *The interaction between relational governance and the adoption of technologies for virtualization and traceability positively influences the cost performance of suppliers*.

The synchronization and accessibility features of network technologies put more emphasis on intelligence at the process level that enhances the dynamic scheduling on the shop floor, and increase coordination of the delivery dates of production orders and the inventory levels, as well as the real-time sharing of details about the transformation stages (Cui et al., 2020; Porter & Heppelmann, 2015). The synchronized interconnection of process entities, based on the seamless sharing of massive data and distributed information across stages, provides a range of opportunities for dynamic collaborations and for relational governance mechanisms that contribute to generating strategic benefits for all the supply chain participants (Büyüközkan & Göçer, 2018; Farahani et al., 2016). The key focus of suppliers on digitalization are transparency, automatic data sharing, and process integration during the ordering, manufacturing, and delivery processes (Mantravadi, Moller, & Christensen, 2018), which allows a quick analysis to be made of their efficiency levels and the accomplishment of the quality requirements.

By reducing data silos and communication barriers between logistics flows, products, equipment, and operating systems, network technologies enable different departments (e.g. production, sales, R&D, IT) to access heterogeneous (and relevant) sources of data and information, be more involved in the innovation of production processes and to find the root causes of manufacturability issues (e.g. design weakness, material issue, etc.) (Cui et al., 2020; Porter & Heppelmann, 2015). Indeed, it is frequent to have integrated digital platforms in the automotive supply chain to manage the supply chain (Gottge et al., 2020). The synchronization and accessibility of these platforms increase the customer's trust that the suppliers will make the best use of the available resources, which are sometimes owned by the customers (i.e. molds), and collaborate for continuous improvement and efficiency (Büyüközkan & Göçer, 2018). Wastes and misalignments with design requirements can easily be detected and logistic processes can be better-synchronized thanks to real-time monitoring, with less manual transactions and a subsequent positive impact on costs. The supplier feels more autonomous in exchanging product- and production-related data appreciating the value of collaborating with the customers, and perceives the impact of the better integration on both the internal processes and on the value delivered to the customers (Liao et al., 2020; Vilko et al., 2012). This relational commitment drives also to an increase in specific investments for productivity gains.

Based on the above reasoning, the following hypothesis is proposed:

HP4. *The interaction between relational governance and the adoption of technologies for synchronization and accessibility is positively associated with the cost performance of suppliers*

6.4 Measures and validity

This chapter adopts measures that are consistent with previous research. For relational governance, this research draws on the work of Zaheer and Venkatraman (2019), followed by that of Blome et al., (2013), who distinguished between the structural and process dimensions of relational governance. Thus, relational governance was measured as a second-order construct, as did Yang et al., (2012). Following Blome et al., (2013), quasi-integration was measured by asking the supplier to rate their involvement in product development, with the customer considered as more important to account for the largest share of the supplier's total turnover. This first-order construct included the following variables: increased responsibilities in new product development, participation in value analysis/value engineering, and advanced simulations of the product. In this chapter, the relational norms mainly pertain to flexibility and solidarity (Yang et al., 2012). Flexibility was measured by asking the suppliers to rate their expectations of customer acceptance and the encouragement of improvement suggestions from suppliers that would reduce production costs but require the customer to modify its design and production activities. Solidarity was measured by asking the suppliers to express their expectations of whether a customer would provide support to the supplier in the case of a competitor offering a product at a lower price, but at the same quality, and whether the customer would allow the supplier to capture part of the savings resulting from cost-targeted suggestions. Trust was measured by asking the suppliers to express their fairness, cooperative atmosphere and benevolent behavior with their main customers.

Contractual governance was measured with a single item scale. The question asked whether the supplier had a formal contract with its most important customer that specified the duties and responsibilities of the supplier with respect to the quality, cost, quantity, and delivery of the components. In the case of a positive answer, the sales managers were also asked to indicate the contract length in years. This was used to measure the contract duration. Based on this, short-term and long-term contractual governance were distinguished each plant was assigned to each sub-group. Specifically, the new variables have "0" if no contract was in place, "1" to contracts of less than or equal to 5 years, and "2" to longer contracts than 5 years). The cut-off point to assign firms to short- or long-term governance was five years because this is considered the average period of the lifecycle of a car model (Tang, 1999). A four-year cut-off point was also considered (Taylor & Wiggins, 1997) and the results illustrated hereafter were consistent. Contracts that extended beyond this period signal a long-term commitment of the customer to continue the relationship with the supplier after the life cycle of a given model.

A set of control variables that could have an impact on cost performance was included. In line with supply chain governance studies (e.g Z. Cao & Lumineau, 2015), the size of the firm, the length of the relationship, and the distance of the supplier from its main customer were included. Moreover, the adoption of enterprise information systems, the percentage of employees with academic degrees, whether the plant offered salary incentives on productivity improvements, the position in the supply chain (e.g. Tier1), and the use of lean practices were also included. Table 10 provides the measurement items and scale of each variable.

Table 10. Measures and validity

Construct	Measure	Operationalization
Cost performance (Blome *et al.*, 2013)	What has been the average annual percent change in your unit costs for this product over the last year and the last three years? • Decreased < 10% (1) • Decreased 3.1 – 10% (2) • Little Change (+/- 3%) (3) • Increased 3.1 – 9% (4) • Increased > 9.1% (5)	Binary: value 1 if respondent answers (1) or (2), 0 otherwise
Physical-Digital Interface Technologies (Ordinal α = 0.91, AVE=0.72, $\chi^2(54)$ =74.608, $p < 0.01$; CFI = 0.921.; CD =0 .973.; RMSEA=0.062) Scale based on Culot *et al.* (2020) and Frank *et al.* (2020)	For each of the following technologies indicate which are adopted: (0/1) • Sensors installed on equipment to continuously monitor work conditions and process parameters (0.54) • Machine vision that allows the computer to inspect images used in metrology and other activities of process quality control (0.75) • Tracking technologies for materials (e.g. RFID, bar codes, QR codes, etc.) to track location and status within the plant for logistic purposes (0.73) • Tracking technologies for products (e.g. RFID, bar codes, QR codes, etc.) to track	Continuous: a sum of five binary variables

	location and status outside the plant for supply chain purposes (0.63) • Human-Machine interface technologies (e.g. augmented reality, virtual reality, wearables, display touch) (0.58)	
Network Technologies Scale based on Culot *et al*. (2020)	How production data (e.g. quality, time, costs, production volume) are collected in this plant? (0/1) • "We use a unified corporate business system that integrates sensors data with data from enterprise information systems (e.g. ERP, MES, CRM, PLM)" AND "Data remains in siloes; it is hard to link together data from different departments (such as HR, operations, sales)" (*reversed*)	Binary
Contractual Governance	Please indicate whether you have a formal written contract with your customer that specify obligations concerning quality, cost, quantity, and delivery reliability (0/1)	Binary: single-item scale
Contract Duration	If you have a written formal contract, please indicate how long is this with your main customer (in years)?	Continuous
Relational Governance	Second order construct (α = 0.73, $\chi^2(54)$ =74.608, p < 0.01; CFI = 0.931.; CD = 0.973; RMSEA=0.062)	
Quasi-Integration Ordinal α = 0.73 AVE = 0.61 Scale based on Blome *et al*. (2013)	Please indicate which descriptions apply to your firm's role in product development for this product. (Please check all that apply) (0/1) • Your business unit provided the majority of engineering hours OR Your business unit took entire responsibility (0.46[a]) • Collaborated with the customer to specify component interfaces or to design-related components of the customer's product (0.49) • Performed finite element analysis or other simulation for this product (0.91) • Participated in Value Analysis / Value Engineering with the customer (0.71)	Continuous: a sum of four binary variables and transformation into 1-5 scale
Relational Norms Ordinal α = 0.65 AVE = 0.51 Scale based on Yang *et al*. (2012)	Suppose your business unit had an idea that would allow you to reduce your costs but would require your customer to make a slight modification in its procedures. How would your customer react? (Please check all that apply) (0/1) • Customer eagerly solicits such suggestions – FLEXIBILITY (0.57) • Customer frequently adopts such suggestions – FLEXIBILITY (0.68) • Customer would adopt the suggestion but would seek to capture some of the savings that would allow us to increase our profitability – SOLIDARITY (0.58)	Continuous: a sum of four binary variables and transformation into 1-5 scale

	How would your customer react if one of your competitors offered a lower price for a product of equal quality? • Help you match your competitor's price efforts – SOLIDARITY (0.56)	
Trust $\alpha = 0.68$ AVE=0.67 Scale based on Liu *et al*. (2009)	Please select the number which best describes your belief that your customer will treat you fairly. • 1= Can't depend on the customer to Treat us fairly; 5= Customer always treats us fairly (0.62) Please indicate the extent to which you disagree or agree with the following statements (1= Strongly Disagree; 5 = Strongly Agree) • Our customer genuinely wants to hear our feedback on how they are performing in their relationship with us (0.74) • We feel that our customer often uses the information we provide to check up on us, rather than to solve problems (*reversed*) (0.83) • There have often been situations of significant disagreement with the customer (*reversed*) (0.77)	Continuous: mean of four Likert variables (1-5)
Size	number of employees	Continuous (log)
Enterprise Information Systems (Ordinal $\alpha = 0.850$, AVE=0.76, $\chi^2(5)$ =20.259, p < 0.001; CFI = 0.929.; CD =0 .914.; RMSEA=0.095)	Which ERP modules are used in this plant? (0/1) (Please check all that apply) • Sales • Warehouse / Logistic • Production • Human Resources • Accounting	Continuous: a sum of 5 binary variables
Multi-Unit Plant	Value 1 if the plant belongs to a multi-plant firm	Binary
R&D Intensity	R&D expenditures to total sales	Continuous (1=0%, 2=1-4%; 3=5-9%; 4=10-24%; 5=25-49%; 6=50-75; 7=75-100%)
% Employees Academic Degrees	% of employees with at least one academic degree	Continuous (1=0%, 2=1-3%; 3=4-5%; 4=6-9%; 5=10-15%; 6=>15%)
Incentives Productivity	Value 1 if the salary contains variables parts related to plant productivity	Binary
Supply Chain Position	The position in the supply chain (i.e. Tier3 or below, Tier2, Tier1)	Continuous (1= Tier3, 2=Tier2, 3= Tier1)
Relationship Length	Expected number of years there is a high probability of continuing to receive orders from the main customer	Continuous (log)

Supplier-Customer Distance	Distance (in km) of your plant from the main customer facility	Continuous (log)
Lean practices (Ordinal α = 0.813, AVE=0.79, $\chi^2(9)$ =14.460, p < 0.1; CFI = 0.946.; CD =0.905.; RMSEA=0.079)	Sum of 0/1 variables related to lean production (i.e. formal lean programs that occurs in teams with the involvement of production workers, management expectations of continuous improvement from production workers, autonomous maintenance, autonomy in stopping production lines in case of defects, suggestions program, value stream mapping)	Continuous: a sum of 6 binary variables

Note: a: Standardized factor loading. AVE = Average Variance Extracted, CFI = Comparative Fit Index, CD = Coefficient of Determination, and RMSEA = Root Mean Square Error of Approximation, Overall Model Fit: $\chi^2(80)$ =110.191, p < 0.001; CFI = 0.911.; CD = 0.992.; RMSEA = 0.086)

This research adopts the measurement quality criteria proposed by Hair et al., (2014) and Forza (2002) to control for the reliability and validity of all the measures used in this chapter. The measured validation was conducted in three steps (Table 10). First, exploratory factor analysis was performed for each multiple-item variable to test the convergent validity, which resulted in factor solution as theoretically expected. Second, the internal consistency method (i.e. Cronbach's alpha) was used to test for reliability. However, for specific constructs (see Table 10), the ordinal alpha method was adopted, which is preferable when constructs are composed of binary items (Zumbo et al., 2007). As shown in Table III, all the constructs have a higher alpha than the minimum suggested accepted threshold of 0.6 (Nunally (Nunally, 1978). Third, a confirmatory factor analysis was performed for each of the constructs to test for convergent and discriminant validity. Specifically, convergent validity was tested through an analysis of the significance and magnitude of the factor loadings. All the factor loadings were highly significant (p<.001) and had acceptable magnitude levels (Hair et al., 2014). Furthermore, the Average Variance Extracted (AVE) for each contrast was greater than the reference point of 0.50. Discriminant validity was assessed by comparing AVE with the squared correlation (Hair et al., 2014). The AVEs of each construct were higher than the sum of the squared correlations with other constructs, thus providing evidence of the discriminant validity. Finally, we checked the overall model fit using the Chi-squared test (i.e., χ^2 per degree of freedom), the comparative fit index (CFI), the coefficient of determination (CD), and the root mean square error of approximation (RMSEA) (Hair et al., 2014). The obtained results showed a good level of fit of the model (Table 10). Table A2 provides the descriptive statistics of the main variables.

Table 11. Descriptive

		Mean	Std Dev	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Cost Performance	0.16	0.37	1															
2	Physical-Digital Interface Technologies	2.52	0.60	0.00	1														
3	Network Technologies	0.60	0.49	0.02	0.17*	1													
4	Contractual Governance	5.21	6.76	-0.14	0.27*	0.09	1												
5	Contract Duration	2.92	1.75	-0.17	0.10	0.09	0.65*	1											
6	Relational Governance	0.68	0.68	-0.04	0.18*	-0.05	0.27*	0.23*	1										
7	Size	148.9	215.6	-0.08	0.45*	0.11	0.33*	0.07	0.20	1									
8	Enterprise Information Systems	2.53	1.87	-0.08	0.43*	0.25*	0.22*	0.01	0.12	0.37*	1								
9	Multi-Unit Plant	0.29	0.45	-0.10	0.35*	0.15	0.48*	0.28*	0.35*	0.58*	0.30*	1							
10	R&D Intensity	2.43	1.31	-0.04	0.12	0.10	0.17*	0.03	0.05	0.04	0.19*	0.13	1						
11	% Employees Academic Degrees	2.89	1.35	-0.03	0.22	0.21*	0.18*	0.00	0.11	0.28*	0.36*	0.28*	0.50*	1					
12	Incentives Productivity	0.46	0.50	-0.13	0.37*	0.19*	0.26*	0.08	0.16	0.37*	0.38*	0.34*	0.07	0.25	1				
13	Supply Chain Position	2.26	0.77	-0.18*	0.25*	0.10	0.40*	0.13	0.25*	0.35*	0.19*	0.30*	0.16	0.33*	0.14	1			
14	Relationship Length	9.89	11.52	-0.11	-0.09	0.09	0.04	0.08	0.11	0.01	0.01	0.10	0.06	0.17*	-0.01	0.22*	1		
15	Supplier-Customer Distance	774.3	1409	-0.05	0.20*	0.07	0.17*	0.09	0.16*	0.23*	0.09	0.23*	0.05	0.07	0.20*	0.06	0.02	1	
16	Lean practices	2.79	1.85	0.10	0.41*	0.07	0.28*	0.06	0.18*	0.46*	0.35*	0.36*	0.15	0.30*	0.31*	0.43*	0.24*	0.05	1

Note: Pairwise Pearson correlations, * significance level at $p < 0.1$

6.5 Results

Table 12 and Table 13 present the results of the logistic regression. Table 14 provides a synthesis of the results and the tested hypotheses.

Table 12. Results of the logistics regressions (IIa)

Dependent Variable: Cost Performance	Model (1) Coefficient (Std. Err.)	Model (2) Coefficient (Std. Err.)	Model (3) Coefficient (Std. Err.)	Model (4) Coefficient (Std. Err.)
Physical-Digital Interface Technologies	-0.122	0.642	0.192	0.372
	(0.482)	(0.752)	(0.604)	(1.038)
Network Technologies	0.297	-0.159	0.644	-0.346
	(0.404)	(0.644)	(0.519)	(0.773)
Contractual Governance	-0.0605	-0.178		-0.309
	(0.935)	(0.887)		(1.044)
Relational Governance	-0.249		-0.253	-0.201
	(0.403)		(0.563)	(0.609)
Contractual Governance X Physical-Digital Interface Technologies		-0.945		-0.042
		(0.848)		(1.111)
Contractual Governance X Network Technologies		0.684		**2.189**$^{+}$
		(0.815)		(1.210)
Relational Governance X Physical-Digital Interface Technologies			**1.998***	**2.865***
			(0.794)	(1.127)
Relational Governance X Network Technologies			0.369	0.165
			(0.493)	(0.483)
Size	-0.271	-0.268	0.091	0.645
	(0.723)	(0.733)	(0.804)	(1.006)
Multi-Unit Plant	-0.0348	-0.0825	-0.938	**-1.625**$^{+}$
	(0.533)	(0.530)	(0.713)	(0.958)
R&D Intensity	-0.0781	-0.0905	-0.365	-0.603
	(0.569)	(0.522)	(0.639)	(0.725)
% Employees Academic Degrees	0.564	0.488	**1.193**$^{+}$	**1.869***
	(0.553)	(0.478)	(0.703)	(0.878)
Incentives Productivity	-0.565	-0.557	**-0.804**$^{+}$	**-1.025**$^{+}$
	(0.416)	(0.409)	(0.486)	(0.591)
Supply Chain Position	**-0.790**$^{+}$	**-0.971***	**-1.511***	**-2.044***
	(0.453)	(0.448)	(0.637)	(0.810)
Relationship Length	-0.302	-0.250	-0.193	-0.0607
	(0.365)	(0.381)	(0.407)	(0.466)

Supplier-Customer Distance	0.581	0.462	0.850	**1.151**$^{+}$
	(0.466)	(0.426)	(0.526)	(0.595)
Lean practices	**1.107***	**1.104***	**1.342***	**1.223**$^{+}$
	(0.533)	(0.526)	(0.614)	(0.692)
Constant	**-2.234****	**-2.034****	**-3.141****	**-3.670****
	(0.733)	(0.694)	(0.720)	(1.127)
Observations	86	88	86	86
Pseudo R^2	0.1998	0.1921	0.3264	0.3787

Note: Coefficients in Odds ratio, Standard errors in parentheses, $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

Table 13. Results of the logistics regressions (IIb)

Dependent Variable: Cost Performance	Model (5) Coefficient (Std. Err.)	Model (6) Coefficient (Std. Err.)	Model (7) Coefficient (Std. Err.)	Model (8) Coefficient (Std. Err.)
Physical-Digital Interface Technologies	-0.0441	0.979	0.192	1.278
	(0.477)	(0.849)	(0.604)	(1.406)
Network Technologies	0.340	-0.399	0.644	-0.872
	(0.417)	(0.693)	(0.519)	(0.862)
Short-Term Contract (<= 5 years)	0.529	0.382		1.210
	(1.111)	(1.134)		(1.481)
Long-Term Contract (>5 years)	-0.453	-1.238		-2.793
	(1.090)	(1.275)		(2.082)
Relational Governance	-0.117		-0.253	0.312
	(0.433)		(0.563)	(0.771)
Short-Term Contract (<= 5 years) X Physical-Digital Interface Technologies		-1.282		-0.0522
		(1.098)		(1.645)
Long-Term Contract (>5 years) X Physical-Digital Interface Technologies		-1.162		-1.097
		(1.167)		(1.598)
Short-Term Contract (<= 5 years) X Network Technologies		-0.225		1.778
		(1.067)		(1.446)
Long-Term Contract (>5 years) X Network Technologies		**2.082**$^{+}$		**6.264***
		(1.234)		(2.480)
Relational Governance X Physical-Digital Interface Technologies			**1.998***	**4.685****
			(0.794)	(1.808)
Relational Governance X Network Technologies			0.369	-0.738
			(0.493)	(0.676)

Size	-0.390 (0.751)	-0.743 (0.838)	0.0913 (0.804)	-0.211 (1.365)
Enterprise Information Systems	-0.815 (0.534)	-0.696 (0.554)	**-1.260*** (0.631)	**-2.902*** (1.193)
Multi-Unit Plant	0.0134 (0.547)	0.335 (0.609)	-0.938 (0.713)	-1.869 (1.244)
R&D Intensity	0.00500 (0.569)	-0.197 (0.586)	-0.365 (0.639)	-0.713 (0.978)
% Employees Academic Degrees	0.649 (0.572)	0.658 (0.523)	**1.193**$^{+}$ (0.703)	**2.853*** (1.181)
Incentives Productivity	-0.611 (0.425)	-0.442 (0.417)	**-0.804**$^{+}$ (0.486)	**-1.418*** (0.716)
Supply Chain Position	**-0.843**$^{+}$ (0.468)	**-1.203*** (0.522)	**-1.511*** (0.637)	**-3.175**** (1.205)
Relationship Length	-0.294 (0.363)	-0.159 (0.422)	-0.193 (0.407)	-0.0608 (0.616)
Supplier-Customer Distance	0.495 (0.483)	0.234 (0.481)	0.850 (0.526)	1.114 (0.831)
Lean practices	**1.193*** (0.560)	**1.347*** (0.617)	**1.342*** (0.614)	**1.801**$^{+}$ (1.101)
Constant	-2.243** (0.734)	-2.132** (0.748)	-3.141** (0.720)	-5.087** (1.700)
Observations	85	87	86	85
Pseudo R^2	0.2089	0.2575	0.3264	0.4873

Note: Coefficients in Odds ratio, Standard errors in parentheses, $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

Table 14. Synthesis of results and hypothesis testing

Hypothesis	Interaction Terms	Expected effects on Cost Performance	Test	Notes
HP1	Contractual Governance X Physical-Digital Interface Technologies	-	Rejected	The coefficients in Model 2 and 4 (Table 12) are negative but not significant
HP1a	Short-Term Contract (<= 5 years) X Physical-Digital Interface Technologies	-	Rejected	The coefficients in Model 6 and 8 (Table 13) are negative but not significant
HP1b	Long-Term Contract (>5 years) X Physical-Digital Interface Technologies	-	Rejected	The coefficients in Model 6 and 8 (Table 13) are negative but not significant
HP2	Contractual Governance X Network Technologies	+	Supported	The coefficient in Model 4 (Table 12) is

				positive and significant
HP2a	Short-Term Contract (<= 5 years) X Network Technologies	-	Rejected	The coefficients in Model 6 are negative while in Model 8 is positive and 8 (Table 13). Both are not significant
HP2b	Long-Term Contract (>5 years) X Network Technologies	+	Supported	The coefficients in Model 6 and Model 8 are positive and significant
HP3	Physical-Digital Interface Technologies X Relational Governance	+	Supported	The coefficients in Models 3 and 4 Table 12) and Models 5 and 6 (Table 13) are positive and significant
HP4	Network Technologies X Relational Governance	+	Rejected	The coefficients in Models 3 and 4 (Table 13) are positive but not significant while in models 5 and 6 (Table 13) are positive and negative but not significant

The difference between Table 12 and Table 13 is related to contractual governance. Contractual governance is presented in Table 12 as a single item scale that indicates the presence/absence of formal contracting, whereas this variable is substituted in Table 13 by a discrete variable that represents the duration of a contract. The same dependent variable (i.e. cost performance) was used in all the models and it includes a set of control variables as described above. As for H1, which states that the interaction between contractual governance and physical-digital interface technologies is negatively related to the cost performance, the result shows a negative but non-significant coefficient in model 3 (column 2 in Table 12) and a positive but not significant coefficient in the model; therefore, H1 is not supported. Similarly, H1a and H1Bb are not supported

Regarding H2, which states that network technologies are positively related to contractual governance, we found a significant positive impact (models 3 and 4 in Table 12); therefore, H2 is supported. H2b, which states the need to have long-term contractual governance to increase the cost performance of suppliers is also supported. However, both hypotheses are only supported in the last columns, that is, model 4 in Table 12 and model 8 in Table 13, which includes relational governance and interaction terms, thus suggesting that relational governance is also needed. In H3, which states that the adoption of physical-digital interface technologies and relational governance are complementary for cost performance, the results show a significant positive impact for both models 3 and 4 (Table 12), thus supporting H3. For H4, which states that the interaction of network technologies with relational governance is positively associated with cost performance, the results do not provide any support as the coefficients are not significant (model 4 in Table 12 and model 8 in Table 13).

Interesting evidence arose from the analysis of the control variables. In this case, the results show that the position in the supply chain is negatively related to the cost performance, thus indicating that suppliers in the “extreme” position of a supply chain (Tier3 and below) have been better at reducing costs than other downstream firms. The distance between supplier and customer was found to be positively related to the cost performance, and it was revealed that the more distant the supplier was from its main customer, the better the results on cost performance (this effect may be a particular aspect of the Italian situation). However, since this result was only found for Model 4 in Table 12 (which includes all the interaction terms), such firms might have leveraged on digital technologies and governance mechanisms to mitigate the negative impact of their distance from customers on the cost performance. The share of employees with an academic degree was positively related to cost performance, thus indicating the importance of human capital in these processes. The adoption of lean practices that favor the internal transparency of information and procedures also has a positive effect. Interestingly, we found that size did not affect the cost performance of suppliers, thus suggesting that even SMEs suppliers can improve their cost performance if they can adapt and complement digital technologies with governance mechanisms.

6.6 Discussion and conclusions

This chapter analyzed the impact of the joint impact of digital technologies classified into two different subsets and relational and contractual governance mechanisms on the cost performance of automotive suppliers.

Contractual and relational governance mechanisms are considered the most effective mechanisms for successful inter-organizational relationships in supply chains (Z. Cao & Lumineau, 2015; L. Poppo & Zenger, 2002). They not only affect the performance of focal firms but also have a substantial impact on the cost performance of suppliers (Jean et al., 2020), especially when the relationship entails highly complex designing, manufacturing, and delivering processes (Gimenez et al., 2012), as in the automotive industry. On the other hand, the opportunities offered by digitalization allow companies to embrace new approaches to manage and govern supply chain processes with novel technological and analytical methods, thereby creating incentives for significant performance improvements and added value (Büyüközkan & Göçer, 2018).

Overall, the results point out how complex is for automotive suppliers to make decisions about digitalization investments in intelligence at the process level (to innovate their product development process in compliance with the compelling design requirements set by carmakers) and to enhance cost performance. On the one hand, to improve cost performance, they have to invest in different and highly specific sets of digital technologies and, on the other hand, to manage their interplay with the governance mechanisms. The results reveal that the features of synchronization and accessibility, which are ensured by network technologies, and contractual governance - in particular in the long-term dimension - are complementary, while virtualization and traceability, enabled by physical-digital interface technologies, are complementary with relational governance in the suppliers' effort to reduce production costs.

Physical-digital interface technologies, thanks to their ability to create real-time information transparency, encourage the development of trust between parties and provide a digital means for collaboration with the customers to pinpoint localized production problems or to find improvement opportunities. On the other hand, network technologies enable full and real-time transparency of process-related information and require long-term contractual governance that signals the commitment of suppliers to not exploit such an integration opportunistically, since it increases the visibility of customers on supplier's processes. These results suggest that, in the case of seamless integration of process information, it is not enough to have relational norms and trust, and that a formal and explicit shared commitment is also required.

Conversely to what was expected, the technologies that enable synchronization and accessibility do not appear to be linked to relational governance. This result is counter-intuitive, considering the growing literature on how the increased connectivity and seamless integration of information enhance further sharing and cooperation that would eventually increase the cost performance of suppliers (e.g. Fatorachian & Kazemi, 2020). Nevertheless, this can be interpreted as an enhanced capability of suppliers to prevent possible forms of opportunistic behavior, due to a closer dependency on customers (as an "indirect effect" of integration), as well as a way of maintaining selected information asymmetries and of leaving space for flexibility in production settings. Although a collaborative relationship allows both parties to obtain benefits, a conflicting element is inevitably embedded in the inter-organizational relationship, especially in the automotive supply chain sector, due to the tendency of firms to protect individual competitive advantages, such as cost performance (Huang et al., 2020).

Theoretical Contributions. This chapter contributes to the existing literature in three main ways. Firstly, this research is focused on the perspective of suppliers, which has largely been neglected in favor of the buying organization (e.g. Blome et al., 2013), in both the literature on the governance of inter-organizational relationships and that on the digitalization of supply chains. The results show that suppliers need both long-term contractual and relational governance in place to generate positive returns (in terms of cost reduction, which eventually also yields benefits for the customer) from investments in digital technologies. Moreover, this study is one of the first to analyze the supply chain considering suppliers in the second or third tiers, who can play a key role in the successful operation of the overall supply chain (Kim et al., 2011).

Secondly, this chapter contributes to the literature on the interplay between supply chain governance and digitalization (e.g. Jean et al., 2020). Prior research has focused on how digitalization, conceptualized in terms of the adoption of enterprise information systems, supports relationship performance, measured as sales growth, market share, and profitability (Jean et al., 2020). This chapter extends this literature by studying the impact on supply chain performance (measured in terms of suppliers' cost performance) pertaining to the interaction between technology forms, and the effectiveness of governance mechanisms in managing and creating value from the enhanced transparency and traceability in the product development process in the context of the digitalization of suppliers.

Thirdly, this chapter confirms the theoretical assumptions of TCE on transaction features, and its applicability as a supply chain efficiency theory (Ketokivi & Mahoney, 2020), by showing the importance of the production costs that still have to be considered, but specifically in terms of the complexity of inter-organizational relationships interlinked with investments in general-purpose technologies, such as digital-physical interface and network technologies.

In doing so, the chapter classified digital technologies in two separate forms, showing the different effects that they may have on governance mechanisms, thus providing evidence on the necessity of more accurate studies on how and under what conditions they can create value at a supply chain level.

Practical Contributions. The investigation framework and the results of the survey may provide a reference for firms and managers of supply chain processes (from operations to sourcing) so they may dedicate their efforts to achieving cost reductions while investing in the specific forms of digital technologies.

The obtained results confirm the ability of automotive suppliers to reduce costs in the presence of a long-term commitment, and on the other hand, how contracts with shorter time horizons have a different output. In this sense, this research also addresses the issue of the investments a manager should make to adapt the internal organization and individual skills, to develop data integration (at both an intra- and an inter-firm level), and to adopt software that can support a long-term relationship with customers. Specifically, physical-digital interface technologies appear to be the moderating technology for relational governance, while network technologies strengthen the effect of long-term contractual governance. Therefore, to fully embrace digitalization, in terms of the combination of technologies, suppliers and customers need to put in place both supply chain governance mechanisms. This requires greater organizational investments in developing relational norms and trust, as well as in drawing up long-term contracts. Doing this will lead to benefits for the entire supply chain, as more efficient suppliers mean more profitable and competitive customers.

Limitations and future research. This research is not free of limitations. First, the sample is limited to the Italian automotive supply chain, and its structure and characteristic could influence results. Future research should extend into other geographical areas. Researchers could perform cross-country comparisons to pinpoint institutional differences and effects of public supporting measures on the adoption of digital technologies. Another research limit is in the measure of contractual governance, which has partially been reduced using contract duration. However, it may be worthwhile to study other contracting characteristics in the context of digitalization, such as contract completeness and the objectives of contract clauses (collaboration vs. control) (Z. Cao & Lumineau, 2015). However, only a few works (e.g. Liem, Khuong, & Canh, 2020) have considered contract duration, and it could represent a key contractual variable that has to be considered to reveal the short- or long-term commitment of suppliers and customers to a relationship and the product development process.

Finally, the focus on cost reduction also suffers from some drawbacks, because it does not capture the value creation behavior, innovation capabilities, quality levels, or responsiveness that are typical outcomes of supply chain collaboration. However, cost reduction is a pressing need for each carmaker, given the highly competitive pressure, and it has therefore been considered a priority in the adoption of digital technologies.

Further research should also investigate the influence of selected managerial practices (e.g. the adoption of lean practices or investments in the training of specific digitization capabilities) that underlie the interaction between the adopted governance mechanisms, and the transparency and visibility enhanced by the combination of physical-digital interface and network technologies, especially in the long term. The patterns of creation and distribution of added value along supply chain processes and tiers should be investigated through longitudinal and qualitative studies. These could also reveal a possible “dark side” of this complex interplay between transactions and technologies in the product development process. Investments in less specific assets and increased data availability could lead to an increased dependence between supplier and customer, or to diminish trust in the other party’s behavior in the long term.

Chapter 7

Making digitalization effective through governance practices with system integrators

7.1 Introduction[6]

The implementation of digital technologies (i.e. digital process innovation) entails a significant degree of uncertainty among the various partners, due to highly specialized knowledge that needs to be integrated to achieve the technological benefits (Kostis & Ritala, 2020). Reducing such uncertainty is critical for ensuring that planned benefits are actually achieved in B2B collaborations. Uncertainty in manufacturing-technological B2B relationships has been studied concerning *behavioral uncertainty* and exchange hazards associated with opportunisms and bounded rationality (Kostis & Ritala, 2020). However, in contemporary industrial relationships involving the exchange of technology and knowledge (Robertson, Casali, & Jacobson, 2012), much of the uncertainty is associated with a difference in cognitive frames regarding definitions, assumption, and expectations of the collective work between the various partners (Weber & Mayer, 2014). This types of uncertainty, defined as *interpretative uncertainty* (Weber & Mayer, 2014), derives not from the transaction characteristics (i.e. asset specificity, frequency of interactions) as for behavioral uncertainty but different relational characteristics of the partners (i.e. the attributes of the parties relative to one another) such as industry membership and technology paradigm. In this thesis, an additional source of interpretive uncertainty is introduced in the context of industrial relationships: **technological challenges** (D. Sjödin, 2019). Interpretative uncertainty raises transaction costs (Weber & Mayer, 2014), due to a wrong understanding of the idiosyncratic design requirements by the technological partner and a lack of knowledge sharing (Rönnberg Sjödin, Frishammar, & Eriksson, 2016). Therefore, manufacturing firms should properly manage their relationship with their industrial partners to reduce the interpretative uncertainty to derive benefits from digital

[6] Some parts of this chapter have been elaborated from a submitted paper to the International Journal of Production Economics with the title "External Knowledge Search, Opportunity Recognition and Industry 4.0 Adoption in SMEs".

technologies (Kamalaldin et al., 2020; Kostis & Ritala, 2020). Among governance practices, market-based or purely contract-based relationships should be avoided as they do not allow to align cognitive frames and reduce interpretative uncertainty (Weber & Mayer, 2014).

The literature on the B2B governance practices between technology partners and manufacturers, for the provision of digital technologies and service innovation, is focused on the "digital servitization" phenomenon. Current studies are mainly qualitative with limited generalizability, which use mainly the perspective of technology providers (Ardolino et al., 2018; Coreynen, Matthyssens, & Van Bockhaven, 2017), rather than those of customers (or manufacturers), and a minor focus on the characteristics of the relationship and its evolution between providers and customers despite a few notable exceptions (Kamalaldin et al., 2020; D. Sjödin, 2019). Recently, it has been shown that as complementary digitalization capabilities evolve in the dyadic B2B relationship the governance practices should evolve from contractual to relational governance (Kamalaldin et al., 2020). However, it remains unclear what triggers the shift to relational governance in B2B inter-organizational relationships. Moreover, there is the need to increase the generalizability of the findings that relational governance combined with the adoption of digital technologies is decisive to increase the cost performance of manufacturers (Kamalaldin et al., 2020). This chapter aims at filling these gaps by investigating the role of digital technologies in determining the required shift from transactional to relational governance to derive benefits from digital technologies. By analyzing the characteristics of the two forms of digital technologies (i.e. physical-digital interface and network technologies) in terms of complexity, novelty, and customization (D. Sjödin, 2019), this chapter analyzes how these technologies enable and require different governance practices between technology partners and manufacturers to derive benefits for the manufacturers. Thus, the research question of this chapter is the following:

What governance practices (transactional vs relational) between technology providers and manufacturing firms reduce the interpretative uncertainty arising from different forms of digital technologies to derive benefits that increase the cost performance of manufacturers?

This chapter analyses two relational governance practices in B2B relationships: co-creation and continuous relationship. Co-creation allows the technological partner to know the specific needs and define better idiosyncratic design requirements, with immediate benefit for a manufacturing firm in terms of clarity of its data flows. Long-term collaborations allow the development of trust, which is relevant considering that as technological implementation unfolds the partners can provide data sharing-based consulting services (Susan Helper et al., 2019). Among various technological partners this thesis focus on system integrators as they represent valuable partners for manufacturing firms as they can represent a single point of contact and therefore develop deep collaborations with them (Barbosa, Salerno, & Pereira, 2019; Lorenz et al., 2020). This chapter uses concepts both from the TCE theory and the KBV. The former argue that whenever there is an exchange transaction cost arise and parties should govern the relationship such that such transaction costs are minimized. KBV adopts a different perspective concerning the purpose of collaborations. KBV argues that keeping transaction costs low as much as possible with governance mechanisms is useless unless companies can exchange and integrate technology and knowledge during the transaction.

7.2. Theoretical Background

7.2.1 Open digital process innovation with system integrators

Recently, innovation scholars found that manufacturing firms tend to use knowledge from different external sources to innovate (Laursen and Salter, 2006), but that when focusing on process innovation they are selective and collaborate deeply with one or few external knowledge sources (search depth) because that it facilitates the exchange of tacit knowledge and its recombination with technological knowledge (Lorenz et al., 2020; Terjesen & Patel, 2017; Trantopoulos et al., 2017). Search depth is preferred over search breadth (i.e. developing collaborations with multiple partners) because introducing digital process innovations is a complex and uncertain endeavor (Gehrke, Bonse, & Henke, 2016), due to the unique properties of digital technologies (Henfridsson & Bygstad, 2013; Youngjin Yoo et al., 2012), which require recombination of tacit and explicit knowledge, complex problem solving, learning by trial and error and systemic changes into several components of a production system (D. R. Sjödin et al., 2018; Trantopoulos et al., 2017).

Studies conducted on Industry 4.0 have found that -among other organizational factors- a firm's openness to actors in the industrial and innovation ecosystem explains the adoption of digital technologies (Agostini & Nosella, 2019; Lorenz et al., 2020). Indeed, different digital maturity models include open innovation among the factors considered important to achieve a higher degree of digitalization (for a review see Sameer Mittal, Khan, Romero, & Wuest, 2018). However, apart from technology adoption, it remains unclear when collaboration with external knowledge sources is decisive to support a focal firm to increase its cost performance (Lorentz et al., 2020).

Among external knowledge sources, system integrators are considered valuable partners by manufacturers for embracing digitalization due to their ability to combine and integrate different technologies based on hardware and software technological elements and to provide plant data and network connectivity (Kahle et al., 2020). A **system integrator** is an enterprise responsible for designing, integrating and implementing externally supplied products and services into a system for an individual customer (Davies, Coole, & Smith, 2017). Concerning digitalization, system integrators combine hardware components and automation software components while providing associated services such as PLC programming, sensors and machine vision installation, human-machine interface set-up, manufacturing execution systems (MES) set-up, and integration with equipment and machine-to-machine communication (Barbosa et al., 2019, Kahle et al., 2020). From the physical installation of equipment and other assistance, system integrators are increasingly delivering network technologies and data analytics services to manufacturers such as data storage and cleaning; data profiling, and mining tools, which allow manufacturers to create a comprehensive stock of their critical data and identify causal-effect chains and potential problems at the root cause; visualization tools; and monitoring tools (Helper et al., 2019). Helper et al., (2019) showed that Industry 4.0 is leading system integrators to evolve their value proposition toward manufacturing companies, by offering one-stop-shopping solutions that range from digital technology implementation to data analytics solutions and consulting about business process reengineering.

7.2.2 Governance practices in digital technologies implementation

The literature on inter-organizational B2B relationships (or governance practices) in the context of digital technologies implementation is focused on "digital servitization". Being at the intersection of two trends i.e. manufacturing servitisation and digital technologies, **digital servitization** refers to the use of digital technologies to deliver services to existing or new customers such as remote maintenance, training, consulting, substituting services, where the product is no longer sold in a traditional transaction but the firm instead sells machine hours with some service level agreements during its operation (Cusumano, Kahl, & Suarez, 2015; A. G. Frank, Mendes, Ayala, & Ghezzi, 2019). In this wide literature, the focus has been mainly on the provider (or technology partner) with a focus on its transformation paths and service configurations (Ardolino et al., 2018; Coreynen et al., 2017). In this stream of literature, the required change of governance practices is touched only partially and with the provider perspective. It is argued that the provider has to shift from transactional, product-centric to relational, customer-centric approaches (Kowalkowski, Gebauer, Kamp, & Parry, 2017). In this respect, providers should develop state-of-the-art capabilities in understanding customers' problems and needs related to a product and in developing new services around them to ensure the combination of the product-service solution (Goduscheit & Faullant, 2018; Kahle et al., 2020; Nylander, Wallberg, & Hansson, 2017). The perspective of customers (or manufacturers) and the related characteristics and evolution is less studied with a notable exception. In a recent qualitative study, Kamalaldin et al., (2020) found that B2B inter-organizational relationships in digital servitization should be based on relational governance as complementary digitalization capabilities among providers and customers evolve. Indeed, for a successful project implementation manufacturing companies need to acquire and progressively recombine complementary knowledge such as big data storage, extraction, transformation, loading, and analytics provided by system integrators with their own business and operational knowledge on the other side. However, apart from complementary capability, it remains unclear what triggers the shift to relational governance practices as manufacturing firms adopt digital technologies. Another stream of literature analyzes the B2B inter-organizational relationship using the TCE theory and in particular highlighting the interpretative uncertainty as a source of high transaction costs (Kostis & Ritala, 2020; Weber & Mayer, 2014). **Interpretive uncertainty** refers to the disagreement on the processes and results of collaborative projects due to relational differences among the collaborating actors (firm and individuals) characterized by different technological competencies, industry membership, and professional seniority (Kostis & Ritala, 2020). Apart from relational differences, this chapter introduces technology characteristics as a source of interpretative uncertainty concerning complexity, novelty, and customization (D. Sjödin, 2019). **Complexity** refers to the extent to which the implementation of technologies requires or affects the interdependence with other parts of production systems increasing the number of interactions among various types of a subsystem (i.e. equipment, information systems) (D. Sjödin, 2019). **Novelty** refers to the extent to which technologies are known to the firm. If new, the firm faces difficulty in understanding how the technologies will behave and predict unexpected problems as well as design activities in advance (D. Sjödin, 2019). **Customization** refers to the degree to which technologies must be adapted to fit the specifics of a particular manufacturing system in use (D. Sjödin, 2019). High interpretative uncertainty is associated with high transaction costs which often result in confusion about design requirements and inputs between partners and lead to considerable delays and even project failure (Kostis & Ritala, 2020). Reducing transaction costs call for hybrid forms of governance practices such as contractual and relational governance but also joint venture (Weber & Mayer, 2014).

This chapter analyzes two relational governance practices: co-creation and continuous collaboration (Athaide & Zhang, 2011; Heide & John, 1990). In this thesis, **co-creation** (or co-design, or co-development), as opposed to unilateral approaches to product development (Athaide & Zhang, 2011), refers to the shared work and joint problem-solving among actors within a dyadic relationship from the design to the realization of the product, service or solution (Athaide & Zhang, 2011; Kohtamäki & Rajala, 2016; D. Sjödin, 2019). Continuous or long-term collaboration, as opposed to short-term collaborations, refers to the extent to which collaboration occurs repeatedly over time across multiple projects (Athaide & Zhang, 2011; Gulati, 1995).

Figure 11 anticipates the research framework, with the developed hypotheses as in the following.

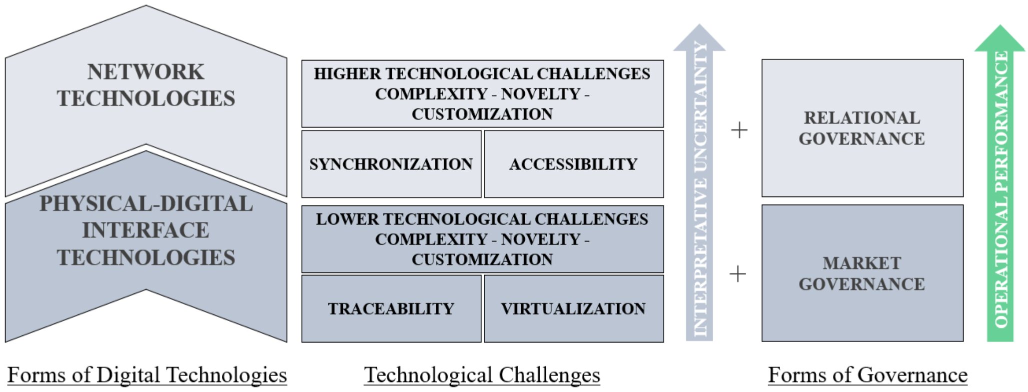

Figure 12. Research Framework (III)

7.3 Hypothesis Development

Physical-digital interface technologies. Despite major advancements (e.g. in miniaturization, connectivity, standardization of communication), physical-digital interface technologies are quite familiar to manufacturing firms since technologies like sensors, machine visions, and human-machine interfaces, exist in manufacturing for decades for operational and automation needs. These technologies, which now have embraced new properties of virtualization and traceability thanks to the above-mentioned advancements, are used for monitoring and controlling the physical equipment (Agarwal & Brem, 2015). The implementation of physical-digital interface technologies is asset-focused (e.g. predictive maintenance) and requires connectivity only for the corresponding assets (Fetterman, 2019). The fact their implementation does not require systemic changes into other parts of the production system means that the complexity of their implementation can be considered low. In a similar vein, the level of customization adaptation of these technologies is low since the implementation of sensors, machine vision cameras or RFID can be installed with a plug-and-play logic. These technologies are quite generic and can be adapted to a large variety of applications (Kahle et al., 2020; Saarikko, Westergren, & Blomquist, 2017).

Since these technologies are available off-the-shelf, as general-purpose and often generic technologies (Saarikko et al., 2017), they do not require relational-based governance practices such as co-creation and continuous collaboration practices but they can be based on market-based governance. Indeed, for effective implementation of these technologies collaborating actively in the development of the technologies or having a prior history of relationships with the system integrators may not be particularly useful.

HP1. *The interaction between co-creation and the adoption of physical-digital interface technologies is negatively related to the cost performance of manufacturers.*

HP2. *The interaction between continuous collaboration and the adoption of physical-digital technologies is negatively related to the cost performance of manufacturers.*

Network technologies. Compare to physical-digital interface network technologies, network technologies are relatively new to manufacturing firms since they require (big) data storage, processing, transformation, and integration skills that are almost lacking in all manufacturing firms with some notable exceptions such as General Electric (Agarwal & Brem, 2015). Network technologies exhibit high levels of complexity in their implementation due to the required combination of different technologies based on hardware and software technological elements and different degrees of network connectivity (Bosman, Hartman, & Sutherland, 2019; Culot et al., 2020). Some open-source big data technologies (e.g. Apache Hadoop, Spark to cite a few), based on standardization, modularity, and interoperability, should partially reduce such complexity, or at least make them more accessible (Eclipse Foundation, 2017), is consolidating in the industry. However, system integration capabilities are needed to integrate different stacks or modules of data architecture. The accessibility and synchronization properties of network technologies require that different physical devices (e.g. equipment, product components) and information systems must be connected and integrated to link data flows thereby increasing the complexity of their implementation. Unlike physical-digital interface technologies, network technologies cannot be simply bought off-the-shelf and implemented with a plug-and-play logic. Instead, since different firms have different information systems and different types of equipment, network technologies need to be customized according to the customer production system requirements

To manage the high levels of interpretative uncertainty arising from higher levels of complexity, customization, and novelty of network technologies, companies should use two relational governance-based practices i.e. co-creation and continuous collaboration for the following reasons.

First, co-creation is required to fill technology capability gaps due to the novelty characteristics as well as to ensure the integration of the network technologies in the customer's production system (Goduscheit & Faullant, 2018; Kahle et al., 2020). Second, co-creation facilitates the development by system integrators of state-of-the-art capabilities in understanding customers' problems and needs related to integrating data flows and provide data analytics (Goduscheit & Faullant, 2018; Kamalaldin et al., 2020). In this respect, system integrators depend on access to their customers' knowledge to customize a process solution to the customer's idiosyncratic design requirements (D. Sjödin, 2019). Based on the above reasoning, the following hypothesis is proposed:

HP3. *The interaction between co-creation and the adoption of network technologies is positively related to the cost performance of manufacturers.*

Continuous collaboration reduces the interpretative uncertainty for the following reasons. First, through continuous collaboration firms can develop a shared specialized vocabulary that assumes importance especially when system integrators arrive from a distant knowledge domain with respect to manufactures. The lack of such a common-knowledge ground between manufacturing firms and their vendors of digital solutions has been indicated to be one of the reasons why investments in information systems and software in Italy have not resulted in a growth of economic value and productivity (Neirotti, Paolucci, & Raguseo, 2011). Second, considering that employing network technologies may imply exchanging data with system integrators sources, continuous collaboration facilitates the development of trust (Athaide & Zhang, 2011; Gulati, 1995), which is a key requirement for effective collaboration especially for SMEs (S. Lee, Park, Yoon, & Park, 2010). Third, continuous collaborations favor the exchange of tacit knowledge that is critical for process innovations (Terjesen & Patel, 2017). In this respect, continuous collaboration facilitates the application of network technologies to the design and manufacturing processes, which are based on trial and error and incremental learning processes.

Based on the above reasoning, the following hypothesis is proposed:

HP4. *The interaction between continuous collaboration and the adoption of network technologies is positively related to the cost performance of manufacturers.*

7.4 Measures

The measure for the adoption of physical-digital interface technologies, network technologies, and cost performance are in section 3.5.1. Co-creation was measured with two questions from the plant survey. In the first question, the survey asks whether firms collaborated with a system integrator for the integration of automation and information systems. Among those that answer "yes", the survey asks what was the degree of involvement of the system integrators in the design and implementation of the integration projects with three items. The following item was used to measure co-creation: "*We define the technical specifications and start the design phase, the system integrator completes the detailed project, develops the integration, and builds the system*".

Similarly, for continuous collaboration, the respondents were asked to indicate the type of relationship they had with system integrators in a question composed of three items. The following item was used to measure continuous "*We typically have an ongoing relationship with a system integrator*". The appendix reports the two questions in their entirety (Table A3).

7.5 Results

Table 15 presents the results of the logistic regression. As for H1, which states that the interaction between co-creation and physical-digital interface technologies is negatively related to the cost performance, the results show a negative and significant coefficient in model 1 and model 2 which differ concerning the presence of the control variables (column 1 and 2 in Table 15). Therefore. H1 is supported. As for H2, which states that the interaction between continuous collaboration and physical-digital interface technologies is negatively related to the cost performance, the results show a negative but non-significant coefficient in model 3 and model 4 (columns 3 and 4 in Table 15). Concerning the three ways interaction between physical-digital interface technologies, network technologies, and co-creation concerning cost performance as the dependent variable, the results show a positive and significant coefficient in model 1 and model 2 (columns 1 and 2 in Table 15). Thus, H3 is supported. As for H4, the results show a positive and significant coefficient in model 3 and model 4 for the three ways interaction between physical-digital interface technologies, network technologies, and continuous collaboration on cost performance (columns 1 and 2 in Table 15). Therefore, H4 is supported by the analysis.

Table 15. Results of the logistics regressions (III)

	(1) Coefficient (Std. Err.)	(2) Coefficient (Std. Err.)	(3) Coefficient (Std. Err.)	(4) Coefficient (Std. Err.)
Physical-Digital Interface Technologies	-0.701	-0.671	-0.492	-0.359
	(0.505)	(0.591)	(0.467)	(0.582)
Network Technologies	-0.155	-0.0602	-0.237	-0.150
	(0.361)	(0.385)	(0.412)	(0.440)
Physical-Digital Interface Technologies X Network Technologies	0.552	0.555	0.103	-0.116
	(0.473)	(0.519)	(0.502)	(0.573)
Co-Creation	-0.219	-0.180		
	(0.358)	(0.429)		
Physical-Digital Interface Technologies X Co-Creation	**-1.268***	**-1.288**$^{+}$		
	(0.572)	(0.669)		
Network Technologies X Co-Creation	-0.0308	-0.0189		
	(0.393)	(0.410)		
Physical-Digital Interface Technologies X Network Technologies X Co-Creation	**0.944**$^{+}$	**1.034**$^{+}$		
	(0.525)	(0.571)		
Continuous Collaboration			-0.183	-0.312

			(0.432)	(0.519)
Physical-Digital Interface Technologies X Continuous Collaboration			-0.503	-0.188
			(0.594)	(0.710)
Network Technologies X Continuous Collaboration			0.0391	0.124
			(0.486)	(0.530)
Physical-Digital Interface Technologies X Network Technologies X Continuous Collaboration			**0.953**$^{+}$	**0.924**$^{+}$
			(0.547)	(0.603)
Size		0.119		0.192
		(0.591)		(0.607)
Enterprise Information Systems		-0.153		-0.0922
		(0.437)		(0.431)
Multi-Unit Plant		0.00236		-0.135
		(0.461)		(0.499)
R&D Intensity		0.130		0.118
		(0.511)		(0.532)
% Employees Academic Degrees		0.0756		0.460
		(0.483)		(0.496)
Incentives Productivity		-0.126		-0.232
		(0.409)		(0.415)
Supply Chain Position		-0.649		**-0.848***
		(0.415)		(0.418)
Constant	-1.502**	-1.615**	-1.642**	-1.874**
	(0.337)	(0.389)	(0.363)	(0.455)
Observations	90	88	90	88
Pseudo R^2	0.110	0.154	0.0935	0.159

Note: Coefficients in Odds ratio, Standard errors in parentheses, $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

7.6 Discussion and Conclusion

This chapter discusses the interplay between governance practices, arising between system integrators and manufacturing firms, and the adoption of different forms of digital technology in the manufacturing firms' effort to derive benefits from digital technologies increasing cost performance.

The review of the literature found two gaps that this chapter aimed to fill. First, studies conducted on the digitalization of the manufacturing firms found that that a firm's openness to actors in the industrial and innovation ecosystem explains the adoption of digital technologies (Agostini & Nosella, 2019; Müller, Buliga, & Voigt, 2020). However, it remains unclear when the collaboration with external knowledge sources increases the cost performance of manufacturing firms (Lorenz et al., 2020). Second, studies on B2B inter-organizational relationships regarding digital servitization has focused mainly on the provider (or technology partner) with a focus on its transformation paths and service configurations (Ardolino et al., 2018; Coreynen et al., 2017) and only partially studied the required changes to governance (Kamalaldin et al., 2020; Kowalkowski et al., 2017).

This chapter shows empirically that the governance practices should be matched with the technological challenges concerning the technologies being implemented to manage the interpretive uncertainty arising from collective work (D. Sjödin, 2019; Weber & Mayer, 2014). As far as the implementation of digital technologies requires limited levels of customization, complexity, and novelty as for physical-digital interface technologies, manufacturing firms can make use of market-based governance practices to derive benefits from digital technologies. By contrast, when firms implement more complex, novel, and custom technologies as for network technologies, they need to develop relational-based governance practices with system integrators to achieve effective implementation of the technologies and therefore increase cost performance.

Theoretical contributions. This chapter makes two distinct contributions to the literature on open process innovations and B2B inter-organizational relationships in digital servitization. Pertaining to open process innovation literature, the chapter provides empirical evidence that sourcing technological knowledge from external knowledge sources is decisive to increase the performance of the recipient firm (e.g. Lorenz et al., 2020; Trantopoulos et al., 2017). However, it adds that this occurs when firms in the dyadic relationship choose appropriate governance practices that match with the technological challenges relative to the technologies that are the objects of the exchange (D. Sjödin, 2019). Second, this chapter contributes to the B2B inter-organizational relationships literature on digital servitization (Kamalaldin et al., 2020) by showing that apart from complementary digitalization capabilities, the forms of digital technologies and related challenges - in terms of complexity, customization, and novelty - plays a key role in determining the relational governance mechanism by reducing interpretative uncertainty arising from collective industrial work.

Practical contributions. Managers of manufacturing firms are encouraged to assess the technological challenges of digital technologies before their implementation and then to choose the appropriate governance mechanism. As manufacturing firms progress toward digitalization, they will rely more on data extraction, transformation, and loading skills that are deeply intertwined with the business processes. As a result, managers are encouraged to establish long-term collaborations and to engage their business translators and data stewards to work with system integrators to provide them with clear design requirements.

Limitations and future research. This study presents two types of limitations. The first limitation pertains to the measure of the governance practices variables which are represented by single-item scales. Future research should develop or integrate measures from research on relational governance and transaction cost economics. Second, this chapter did not test the effectiveness of contractual governance during the implementation of digital technologies (Kamalaldin et al., 2020). It could be the case the properly defined contract clauses can increase the willingness of manufacturing firms to increase data sharing toward system integrators determining a safeguard for opportunistic behaviors.

Chapter 8

Making digitalization effective: the impact of country and institutional setting

8.1 Introduction[7]

The extent to which digitalization happens is a result of different elements including the types of management practices and digital technologies adopted (the scope of this thesis so far), the industry environment (Mithas, Tafti, & Mitchell, 2013), and country-level policies (MacDougall, 2014). This chapter focus on the last element. The legal and infrastructural conditions of a country can exhort a great impact on the way digitalization is tackled and therefore its impact on the productivity of firms operating under the institutional laws and setting of the country (Hanelt et al., 2020). Different countries have introduced different national plans to increase the investment of private sectors to retain competitiveness at the country level such as the "Manufacturing USA" and the "Industria 4.0" in Italy. These plans are focused on increasing public-private partnerships among industry, university, and government agencies on cutting-edge technologies and the provision of tax incentives to stimulate technological investment. Industry 4.0 can be perceived as a policy-driven innovation discourse aimed at institutionalizing a Triple Helix model of collaboration between government, academia, and enterprises (Reischauer, 2018). However, since the starting point of each country in terms of institutions are different (e.g. education system, innovation policies, government), the extent to which digitalization is approached by firms is likely to be different. Using a unique dataset of automotive firms operating in two advanced countries i.e. Italy and the US with a fully comparable survey, this chapter aims to report some comparative descriptive statistics on the adoption of management practices and digital technologies in these countries and providing some explanations and implications of these differences.

The research question of this chapter is the following:

[7] Some parts of this chapter have been elaborated from: (i) a conference paper presented to the GERPISA 2020 International Colloquium in June 2020 with the title "Digital Transformation of the Italian and US Automotive Supply Chains: Evidence from Survey Data"; (ii) a working paper with the title "Organizational Architecture and the Adoption and Use of New Technologies: Evidence from Italian and US Survey Data"

Are there different national approaches to digitalization in two major industrialized nations like Italy and the US that reflect institutional differences?

The analysis included in this chapter is preliminary because it does not directly study the institutional variables such as culture, social norms, industrial policies, and educational systems, trade unions, etc. This chapter is structured as follows. First, the Italian and US automotive industries are briefly reviewed. Second, some comparative statistics mirroring the structure of this thesis are provided below. The chapter concludes with a discussion of the findings.

8.2 The US and Italy automotive industry

The US automotive industry. There are several types of players in the US auto industry. The automakers (e.g., Ford, Toyota, Volkswagen) design, market, and assemble cars. They preside over a supply chain that includes large "first-tier" suppliers (suppliers who supply directly to automakers), who are in turn supplied by smaller second-tier suppliers, who are supplied by third-tier suppliers, etc. Automakers capture 70-80 percent of the market capitalization in the industry (Jacobides, MacDuffie, & Tae, 2016), though this figure overstates their share since many small suppliers are privately held. About 1.5 million people are employed in the US auto parts sector, about four times as many as are employed directly by automakers (Susan Helper, Miller, & Muro, 2018). Automakers rely on a common set of suppliers, which is beneficial in that suppliers can specialize in narrow areas, such as automotive seating. Each automaker benefits from the reduced fixed costs and increased access to suppliers' experience making similar products for other customers. On the other hand, lead firms have reduced incentive to invest in upgrading the supplier's capabilities if that supplier may also use those capabilities to serve a competitor. In the past, automakers used purchasing strategies selected for suppliers with relatively low bargaining power. The US-owned automakers (GM, Ford, Chrysler) used short-term contracts with many suppliers per part and took complicated functions (e.g. product design and sub-assembly) in-house. In contrast, Japanese-owned automakers (Toyota, Honda) and their suppliers have emphasized more collaborative relationships. In recent years, US-owned automakers have converged a bit toward Japanese practice (Perspectives, 2007). However, a legacy of small, weak suppliers remains a legacy that complicates the adoption of modern automation and digitalization practices. Helper and Kuan (2017) documented this weakness, including failure to adopt proven managerial techniques. One-third of auto suppliers have fewer than 500 employees, and fewer than half of these small firms have adopted quality circles (in which production employees gather regularly to troubleshoot quality concerns), and only two-thirds of them self-report that they consistently perform preventative maintenance. A quarter of small automotive firms employ no engineers.

The Italian automotive industry. Italy is one of the leading EU countries for the automotive industry, following Germany and France in terms of sales volume. The Italian automotive component industry is composed of a large share of SMEs accounting for 91% (employment less than 249 employees), while large enterprises (more than 250 employees) accounts for 9% (Barazza & Coccimiglio, 2019).

There are about 2200 auto suppliers in Italy, with about 162.000 people employed in the Italian auto parts production industry, about twice the 96.600 employed directly by automakers (ANFIA, 2018). Concerning turnover, auto suppliers account for about $82 Bn, three times as much as automakers ($27 Bn), while value added at factor cost is $13 Bn, almost doubling automakers ($7.5 Bn). For Italian auto suppliers, 35-40% of the turnover comes from FCA, followed by Volkswagen (about 20%), BMW, RNM, and Daimler (about 5-10% each), and some other automakers (15-20%). Due to its predominant role in the Italian market, FCA has enough bargaining power to require suppliers to adopt WCM (World Class Manufacturing, the FCA label for Lean Production) practices, investing time and resources in upgrading it. More detail on the Italian automotive industry including digitalization trends can be found in chapter 4.

8.3 The comparative research sample

The US survey has been undertaken in 2017 and 2018 by Prof. Susan Helper of Case Western University, Prof. Robert Seamans, and Raphael Martins of New York Stern University. The survey was carried out with the support of major industrial automotive associations. The survey response rates were 1-2% for the 2011 survey resample, and 15-30% for the sample of firms that were part of the automakers' parts suppliers' associations. The Italian automotive industry survey was undertaken in 2018-2019. For details on the Italian automotive survey see chapter 4. After the integration of the US and Italian datasets (some questions had to be changed to reflect the specificities of each country e.g. in terms of workforce structure), a dataset of 90 US plants and 99 Italian plants is used to compare national approaches to digitalization. The sample is structured as in Table 16. In the US, a firm is considered "SME" when it has less than 500 employees, while in Italy such definition pertains to firms with less than 250 employees. According to this definition, the sample is composed of 70% (US) and 83% (Italy) SMEs. While if we look at firms with less than 250 employees, there is 42% in the US and 83% in Italy samples. In line with the population, the average number of employees per analyzed plant is 405 for US firms, and 109 for Italian firms.

Table 16. The Italy and US research sample by firm size

	Total plants	**Number of employees**		
		<250	251-499	>=500
US	90	38	25	27
IT	99	82	8	9

8.4 Comparative descriptive statistics

The first comparative statistics that are reported are related to the main challenges faced by Italy and US auto plants (US firms were presented with a choice set of seven challenges; Italian firms were presented with a choice set of ten challenges). Firms in the two countries are aligned in identifying the three they are most worried about, shown in Figure 13: (1) Finding workers with appropriate skills, (2) building employee engagement, and (3) implementing advanced technology.

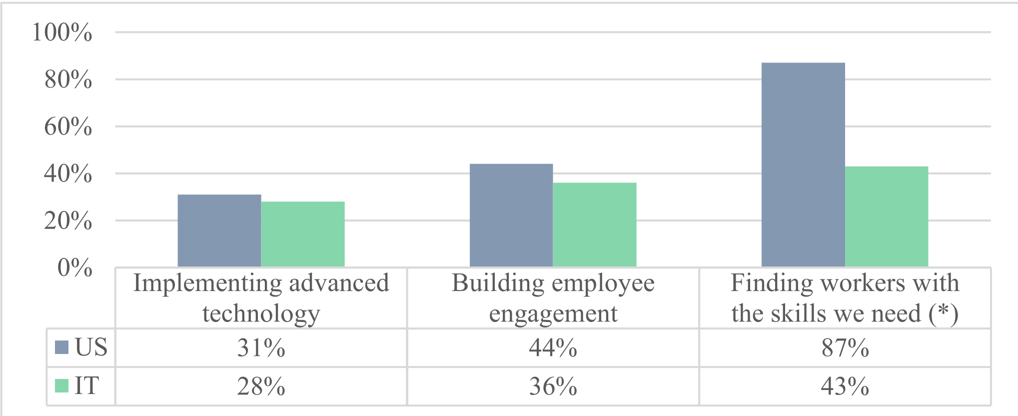

Figure 13. Main challenges by country (% of plants)

As indicated in Figure 13, US plants are approximately twice as likely to report that finding workers with skills needed is a challenge. This is also the only item for which the means are statistically different tested with an ANOVA.

Figure 14 reports the level of adoption of physical-digital interface technologies. The US shows a statistically significant higher number of firms adopting physical-digital interface technologies, except for automated parts tracking (Figure 2). These differences are driven by plant size differences across the two countries, as US firms are larger than Italian firms, on average. Bigger sizes are associated with higher production volumes, which in turn call for a higher share of equipment with sensors and machine vision technologies.

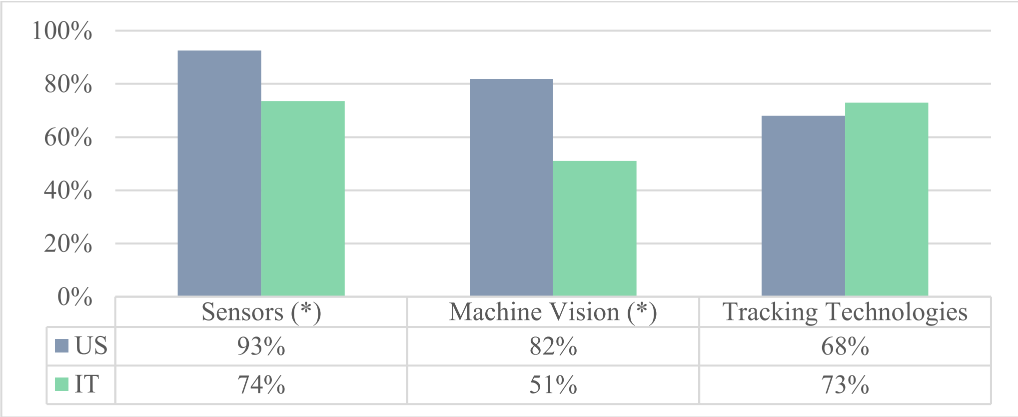

Figure 14. Adoption of physical-digital interface technologies by country

Despite more widespread adoption of digital technologies, manual and “siloed” data collection is widespread among US plants, while it does exist a small but greater share of Italian plants (21%) that are automating and integrating data collection through network technologies and perceived less functional silos on data (24%) (Figure 15).

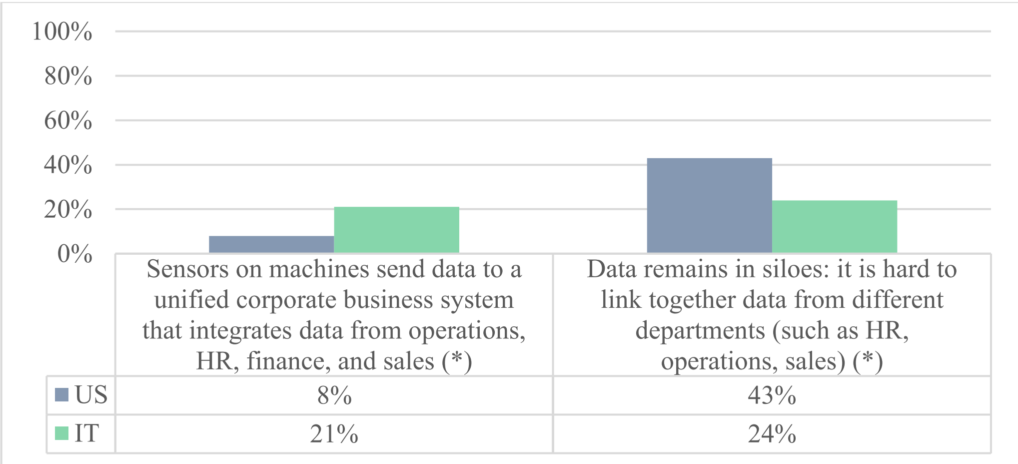

Figure 15. Adoption of network technologies (% of plants) by country

Such a higher inclination towards automating and integrating data collection of Italian plants is correlated with higher data-driven decision-making compared to the US. The Italian plants are more likely to base their decisions on the analysis of data (54%) compared to the US where intuition-driven decision-making is more diffused (Figure 16).

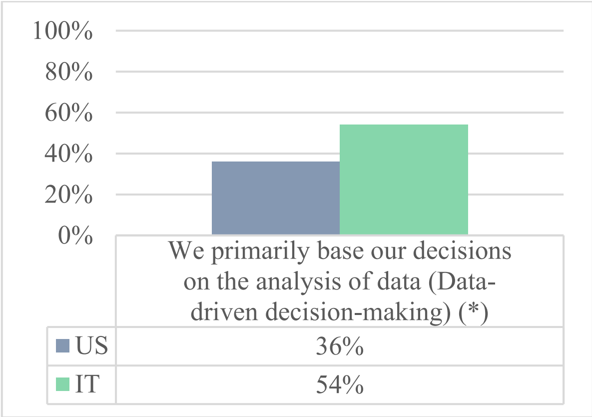

Figure 16. Data-driven decision-making by country

In the following, it is reported an analysis made on the type of tasks assigned to production workers available in other sections of the plant survey concerning the one used in this thesis so far. This would help to understand better the national approaches to digitalization. An explorative factor analysis distinguished two factors: **autonomy in equipment management** and **involvement in continuous improvement.** The former factor refers to the autonomy given to production workers in managing production equipment including activities such as set-up equipment, modify programs on computerized machines, and diagnose equipment problems. The latter refers to the empowerment of production workers in continuous improvement such as using quality data to recommend improvements and make improvements in their methods of operations. Through these two dimensions, managers empower production workers to use their contextual knowledge of production processes to manage equipment and bring improvement ideas. The items composing the measures and the results of factor analysis are shown in the appendix (Table A4). The polychoric factor analysis, based on polychoric correlations, was used since the measure is composed of items with different scales (Zumbo, Gadermann, & Zeisser, 2007). The values have been later normalized on a scale ranging from 0 to 1. Figure 17 shows that the US plants give more autonomy in equipment management, while Italian firms involve more production workers in continuous improvement processes.

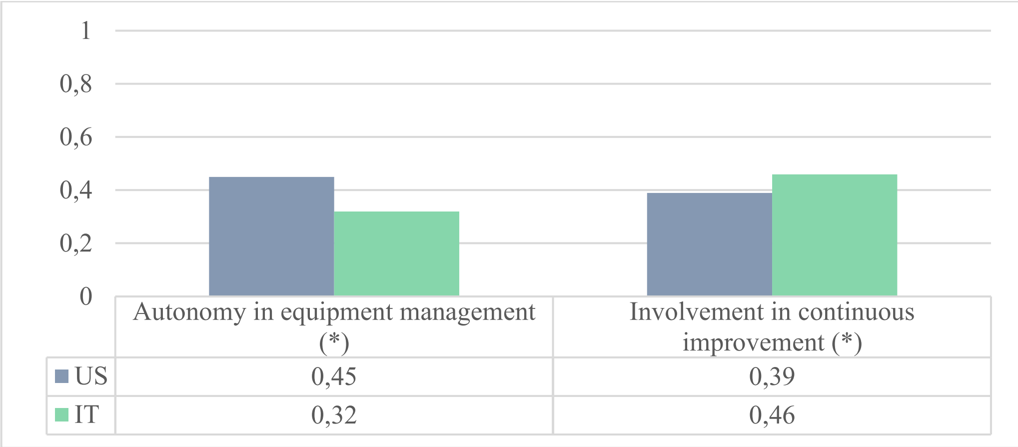

Figure 17. Tasks assigned to production workers by country

Concerning collaboration with system integrators, there are not any statistically significant differences either regarding the share of plants that collaborated with system integrators (Figure 18) or the relational-based governance practices with them (Figure 19).

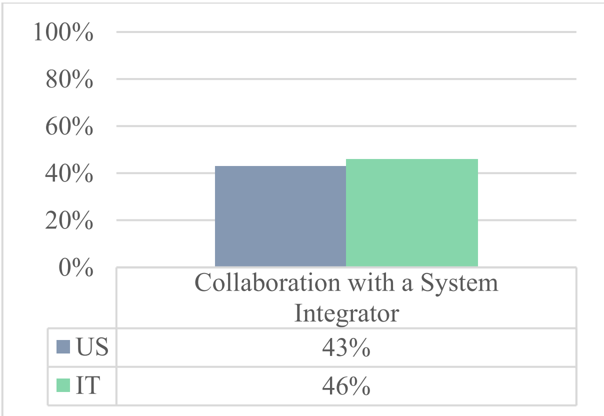

Figure 18. Collaboration with system integrators by country

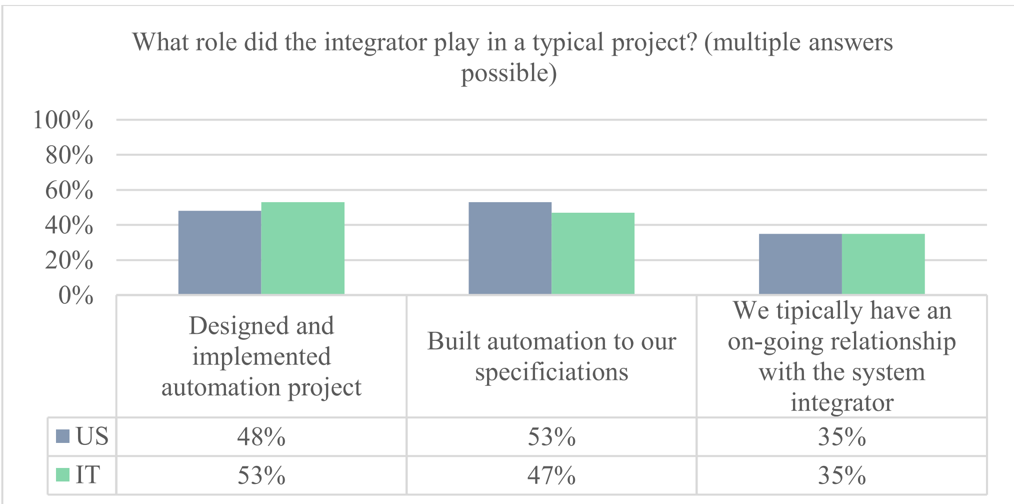

Figure 19. Collaboration practices with system integrators by country

Concerning customer relationships, the survey investigated the level of collaborative problem-solving involving the exchange of data and information amongst companies by asking firms to which extent they agree with the following statement: “We feel that our customer often uses the information we provide to check up on us rather than to solve problems.”. Results, shown in Figure 20, are lightly skewed towards disagreement and neutral opinions. Therefore, negative impressions regarding behavioral uncertainty of customer utilization of shared data represent a minority of answers, though not so irrelevant getting approximately 30% in both countries. No significant differences were found in terms of agreement and disagreement between the two countries.

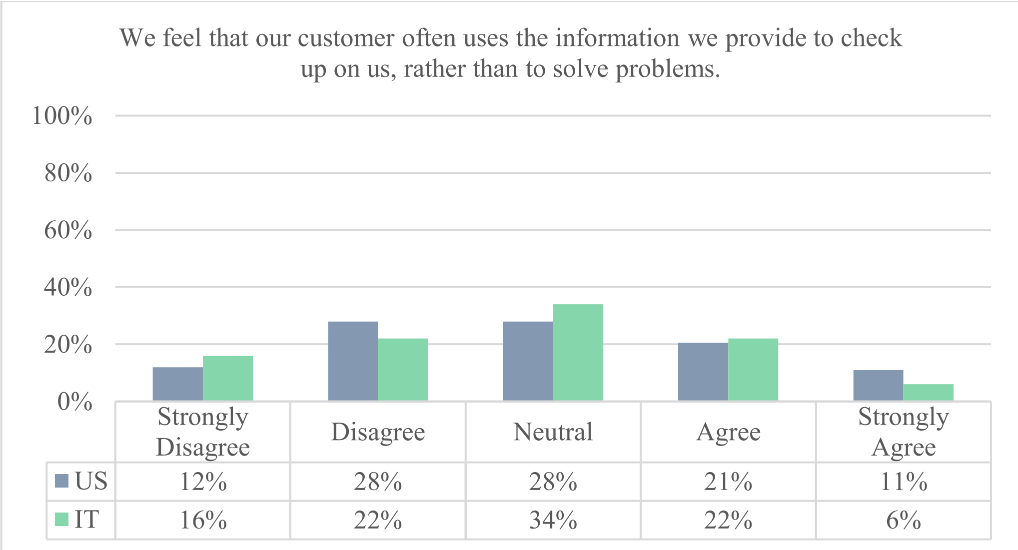

Figure 20. Customer use of shared information by country

8.4 Discussion and conclusion

From the comparative descriptive statistics shown in the previous section, it is possible to distinguish some national approaches to digitalization that reflect institutional differences. The US plants have invested more in physical-digital interface technologies compared to Italian plants due to their bigger size and therefore more equipment and production lines. However, the fact that US plants have adopted fewer network technologies and intuition-driven decision-making approaches seems to suggest that these technologies are used for automating processes rather than for collecting and analyzing data to improve the processes. In the US, this trend could be caused by a lack of workers with the skills in both data analysis and domain knowledge on production processes (e.g. milling, welder, etc.) which could have pushed US companies to prefer a technology-push approach.

The Italian plants are suffering from structural weaknesses characterized by several micro and small and medium-sized enterprises which is a key explanation for the lower investment in physical-digital interface technologies. However, it was found that Italian firms seem to be better positioned concerning the US with more automated and integrated data collection and less manually input data. The results seem to suggest the higher propensity of Italian firms to make decisions based on data probably due to higher availability and quality of data.

The fact that US firms are more technology-intensive than Italian firms seem to explain why US firms empower their production workers with more autonomy in equipment management. By contrast, Italian firms rely more on their employees to bring continuous improvement initiatives and less on technology-driven initiatives. This chapter contributes to the digitalization literature concerning the legal and infrastructural conditions of a country (Hanelt et al., 2020), by showing that institutional differences of the country have an impact on the way digitalization is approached. The institutional forces that drive this difference seem to be caused by levels of the skills gap and structural conditions of the country in terms of the size of firms.

This analysis provided in this chapter has two main limitations. First, some of the explanation of the correlation between findings are tentative and would require further research to be tested. Second, the analysis included in this chapter is preliminary because it does not directly study the institutional variables such as culture, social norms, industrial policies, educational systems, trade unions, etc. Future research could extend this analysis by investigating quantitatively or quantitatively the effect of institutional variables on the digitalization approaches of firms including to what extent the best practices identified in this thesis are replicable to other countries.

Chapter 9

Summary, conclusions, and implications of the research

9.1 Discussion of research findings and theoretical contributions

This Ph.D. thesis aims at understanding the complementarity between organizational practices and digital technologies on the cost performance of manufacturing firms. While digitalization pertains not only to “do things better” through process innovations but also to “do new things”, through product and service innovations, this thesis focused on the former objective being one of the most expected outcomes from the investment in digital technologies (PwC, 2018) and the focus of policy-driven innovation discourse such the Italian Industry 4.0 National Plan. Overall, this thesis found that the existence of different bundle of technologies that offers different opportunities which managers should be aware of and learn to distinguish them and in particular their digital properties. The impact of digital technologies on cost performance is moderated by the implementation of a bundle of management practices including a change of decision-making approach toward data analysis, change governance approaches toward both relational and contractual mechanisms when collaborating with customers and system integrators.

Rooted in a contingent perspective (Sousa & Voss, 2008), the main argument used throughout this thesis is the fact that trying to focus on the adoption of digital technologies is useless, even harmful unless managers foster the development of new organizational practices including governance practices, decision-making approaches, resources, activities, capabilities, and strategies that will allow the creation of value from digitalization (Björkdahl, 2020).

From a high-level perspective, this thesis contributes to the literature that analyzes the impact of digital technologies on cost performance (Lorenz et al., 2020; G. L. Tortorella, Giglio, & van Dun, 2019; Trantopoulos et al., 2017), by investigating two organizational practices: decision-making and governance practices with customers and system integrators.

Since this thesis adopt a phenomenon-based research approach (Von Krogh et al., 2012), the first background section (section 2) of this thesis focused on characterizing the digitalization phenomena. The main outcome of this section was the identification and discussion of the properties of two different forms of digital technologies: physical-digital interface technologies and network technologies. Traceability and virtualization characterize the first technology bundle, while accessibility and synchronization are the properties of the second technology bundle. The implications of these digital properties for decision-making and governance practices have been later used in the following sections when discussing the interplay between organizational practices and digital technologies on firms' efforts to increase cost performance. Integrating operation management (e.g. Culot et al., 2020; Alejandro Germán Frank et al., 2019) and organization literature (e.g. Kallinikos et al., 2013; Y. Yoo, 2010), the identification of these digital properties makes an important contribution to this literature by providing succinct yet comprehensive types of digital properties paving the ways to other studies that can use these properties as operant resources that enable change to organizational practices and entrepreneurial activities (Lusch & Nambisan, 2015; Nambisan et al., 2019).

Following the abductive approach of theoretical contextualization in which results and theory are investigated simultaneously (Bokrantz, Skoogh, Berlin, Wuest, et al., 2020; Ketokivi & Mantere, 2010), the second background section (section 3) of this thesis provided a brief discussion of the main theories used in this thesis: Contingency Theory, Information-Processing View, the theory of Organizational Sensemaking, the Knowledge-Based View and the Transaction Cost Economics. In this respect, this thesis answers a recent call to study digitalization and digital transformation using different theoretical models and approaches concerning the one used in the IT-related organizational literature (Hanelt et al., 2020). Using theoretical contextualization and a phenomenological research approach, this thesis contributes to the wide digitalization literature by proposing these relatively new research methods and approaches to investigate organizational change (von Krogh, 2018; Von Krogh et al., 2012), while incorporating the specific traits of digital technologies (Hanelt et al., 2020).

The third background section (chapter 4) of this thesis focused on the empirical research setting of the research: the automotive industry. In this section, the rationales of using the automotive industry as the research, the role of automotive suppliers, the digitalization trends of the industry, and the method of research have been also discussed. The descriptive findings from 102 questionnaires, fulfilled by human resources, plant managers, and sales managers of Italian automotive suppliers and a literature review found the automotive industry is pioneering the adoption of new digital technology and organizational transformations. However, many challenges and uncertainties remain ahead including, besides the achievement of operational outcomes such as quality and efficiency, finding and attracting workforce with data extraction, transformation, and analysis skills, convincing employees to trust data and make data-driven decisions, trust customers in the use of exchanged data and information, and advance strategic collaboration with system integrators.

We often hear from the press that data, a key characteristic of the digitalization phenomenon, is the new oil. Across all industries, experts, and well-known newspapers such as The Economist and Forbes agree that data is an increasingly valuable resource (Economist, 2017; Gilbert, 2017). However, data by themselves will not solve business problems. This thesis highlights that, alongside digital-driven generated data through the properties of digital technologies, companies should manage their organizational variables in terms of data-driven decision-making approach, relational and long-term contractual governance with customers, relational governance practices of co-creation and continuous collaboration are required and enabled management practices.

Concerning **decision-making approaches**, chapter 5 found that the data-driven decision-making approach widely diffused is the key value-creating organization to make a return on the investment from digital technologies. Compared to the intuition-driven decision-making approach that drives fast, non-conscious, holistic, and experiential decisions, the data-driven decision-making arises through slow, conscious, sequential, and analytical decisions. Hypothesizing that physical-digital technologies via traceability and virtualization and network technologies via synchronization and accessibility respectively increase the analyzability and reduce the equivocality of events (such as machine breakdown or design changes), chapter 5 found that data-driven decision-making is a required and enabled practice by digital technologies to increase the cost performance of manufacturing firms. This section contributes to the literature on decision-making approaches (Flores-Garcia et al., 2019) and data-driven decision-making literature (e.g. E Brynjolfsson et al., 2011; Provost & Fawcett, 2013). The contribution lies in the identification of the value of a data-driven decision-making approach when adopting a new generation of digital technologies. Furthermore, it shows that the heterogeneity in the characteristics of digital technologies exhorts a different impact on the conditions (i.e. analyzability and equivocality) under which data-driven decision-making is a superior decision-making approach over intuition-driven decision-making.

To make digitalization effective inside the factory, this thesis found that - an increasing rate of technology complexity, customization levels, and novelty of the two different forms of digital technologies (from physical-digital interface technologies to network technologies) – manufacturing firms should rely on relational **governance practices** based on co-creation and continuous collaboration with technology partners like **system integrators** that allow the reduction of transaction costs and also the sharing of technological and domain knowledge but also of data for the provision of data analytics services. This section made two distinct contributions to the literature on open process innovations and B2B inter-organizational relationships in digital servitization. Pertaining to open process innovation literature, this thesis provided empirical evidence that sourcing technological knowledge from external knowledge sources increases the performance of the recipient firm (e.g. Lorenz et al., 2020; Trantopoulos et al., 2017) as far as firms in the dyadic relationship choose appropriate governance practices that match with the technological challenges relative to the technologies that are the objects of the exchange (D. Sjödin, 2019). Second, this thesis contributes to the B2B inter-organizational relationships literature on digital servitization (Kamalaldin et al., 2020) by showing that apart from complementary digitalization capabilities, the forms of digital technologies and related challenges - in terms of complexity, customization, and novelty - plays a key role in determining the relational governance mechanism by reducing interpretative uncertainty arising from collective B2B work.

Concerning **governance practices** with **customers**, this thesis found that the traceability and virtualization properties of physical-digital interface technologies enhance the relational governance based on quasi-integration, relational norms, and trust. For instance, the traceability and virtualization of product lifecycle data allow suppliers to match that the promise they made in the design phase regards product specifications with the delivery, that is what is produced in the manufacturing phase. Concerning the implications of network technologies, this thesis provides the first evidence of the dark side of digital technologies determined by increased accessibility and transparency which increase the behavioral uncertainty of customers regarding data and information sharing. The thesis found that only when there are safeguarding mechanisms in place such as long-term contracts the network technologies have a positive effect on the supply-chain relationship. Taken together, the different forms of digital technologies and governance practices reduce the transaction costs among the partners and therefore increase incentives for suppliers to engage in process innovation activities aimed at reducing production costs. This section contributes to the literature on the interplay between supply chain governance and digitalization (e.g. Jean et al., 2020). Prior research has focused on how digitalization, conceptualized in terms of the adoption of enterprise information systems, supports relationship performance, measured as sales growth, market share, and profitability (Jean et al., 2020). This chapter extends this literature by studying the impact on supply chain performance (measured in terms of suppliers' cost performance) pertaining to the interaction between technology forms, and the effectiveness of governance mechanisms in managing and creating value from the enhanced transparency and traceability in the product development process in the context of the digitalization of suppliers.

Finally, this thesis found some national approaches to digitalization by comparing Italy and the US automotive components industry reflecting institutional differences between the two countries. Using a comparable sample, this thesis found that Italian auto plants, while adopting less physical-digital interface technologies concerning the US due to smaller firms' size, show a higher diffusion of network technologies and a data-driven decision-making approach. Due to the higher empowerment of workers in continuous improvement, the Italian approach to digitalization seems more a human-centered approach with a focus on data analysis and data integration. By contrast, the US approach to digitalization is therefore the use of technology due to a critical skill gap. This approach seems directed more toward automation than digitalization giving workers autonomy in managing equipment. These findings contribute to the digitalization literature concerning the legal and infrastructural conditions of a country (Hanelt et al., 2020), by showing that institutional differences of a country have an impact on the way digitalization is approached.

Overall, the thesis shows how complex is for automotive suppliers to make decisions about investments in intelligence at the process level and to enhance cost performance in the digital transformation context. On the one hand, to improve cost performance, they have to invest in different and highly specific sets of digital technologies and, on the other hand, to change decision-making approaches, to manage their interplay with the governance mechanisms with technological partners and customers.

9.2 Practical implications for managers: transformation paths

Manufacturing firms live in uncharted waters where new technology trends, sustainability requirements, globalization threats, new unforeseen events such as COVID-19 increase dramatically the Volatility, Uncertainty, Complexity, and Ambiguity of events in terms of demands, customer behavior, technology opportunities, etc. In this respect, the VUCA framework (Schoemaker, Heaton, & Teece, 2018) (from Volatility to Vision, Uncertainty to Understanding, Complexity to Clarity, Ambiguity to Agility) is used to suggest four main areas of concrete actions to undertake such transition as effective as possible. One significant way to govern the processes and reduce the impact of VUCA elements and not being overwhelmed is to instill the data-driven decision-making as a philosophy inside organizations at different levels. An understanding that information technology companies and Silicon Valley-based start-ups have already understood very well and to which manufacturing firms should benchmark with (Stephan, 2020).

The following recommendations to managers concern the different digital transformation paths that firms can undertake toward a fully digital integrated factory (i.e. Smart Manufacturers), once physical-digital interface technologies have been implemented (Figure 21). The recommendations start with section 4 on decision-making approaches and then develop on the findings of section 5 and section 6 on governance practices with customers and system integrators.

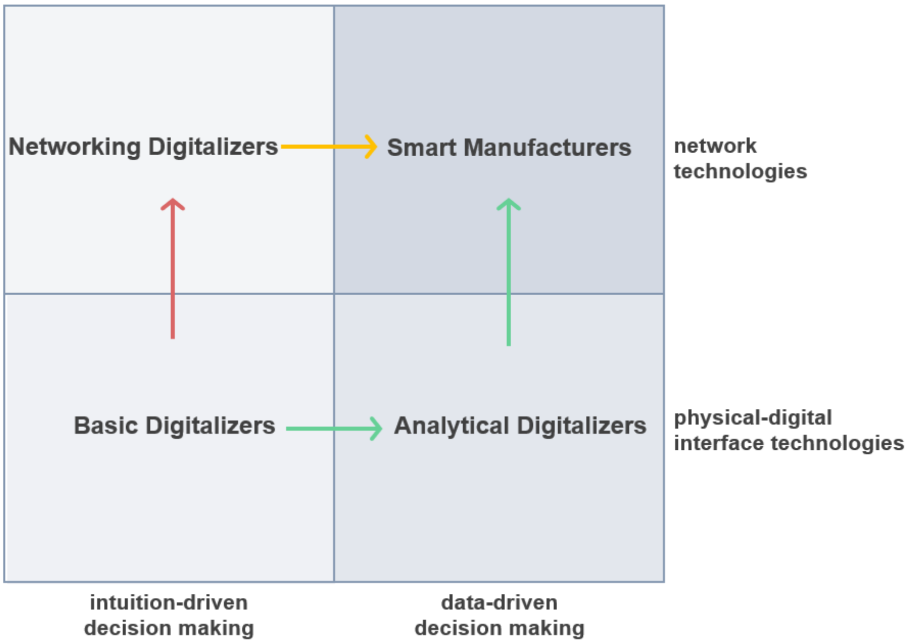

Figure 21. Suggested digitalization paths

9.2.1 From Volatility to a data-driven Vision (leaving aside intuition, not experience)

Whether just digitalized or already interconnected, the first thing to do is to instill a data-driven philosophy throughout the whole organization. If a firm falls into the Basic Digitalizers category, it is suggested a preferred path – "first right, then up" – in which managers support the diffusion of analytical and data-driven mindset in their workers. This does not mean that managers should neglect their domain expertise and experience, but that should encourage them in applying synergistically both data and domain knowledge, in which however data should play a primary role. Some scholars argue that with big data handled by network technologies, the scientific method is becoming obsolete (Anderson, 2008), which may be true in the context of information technology companies (e.g. Google, Amazon, Facebook, Netflix) focused on forecasting the behavior of customers, but not in manufacturing. Indeed, there is another culture of data analysis other than forecasting: modeling, which is focused on process understanding (i.e. that generates scientific knowledge) for troubleshooting, process improvement, and optimization, in which both domain knowledge (to formulate the right hypothesis and ask relevant questions) and data analysis (to evaluate hypothesis) are needed (Ferrer, 2020). By increasing the understanding of processes, modeling can bring significant benefits in predictive applications for instance for machine health status.

A firm, however, could have already digitized and connected (for instance by exploiting national investment plants that offer fiscal incentives) before instilling a data-driven philosophy and might be experiencing some tensions typical of the "Networking Digitalizers" cluster. Managers are encouraged to undertake this "leftto-right" path immediately unless they do not want a pilot project stuck in purgatory (Behrendt et al., 2018). Doing a step back, not insist on the interconnection, but rather focus on the data-driven philosophy is the right management practice (Tudor & MacDonald, 2020). In the "unstable" cluster of the Networking Digitalizers, such a vision change might be more expensive and harder, so managers should consider putting much effort and resources to smooth and accelerate the transition toward a data-driven firm. Shifting from an intuition-driven to a data-driven culture is a challenge for all modern enterprises (Martínez-Caro et al., 2020). So how to shift from an intuition-driven to data-driven culture? From the analysis of the case studies, the firms that were initiating this journey, and those already data-driven, agree that such a process requires time to change culture and mindset. Here are the main recommendations, drawn from the qualitative and quantitative findings, to prevent volatility and uncertainty through, respectively, a formalized data-driven vision and an increased understanding.

Formalize the data-driven Vision by investing in lean production practices. The results of the survey show a high correlation between data-driven approaches and lean practices, both in the case of studies and in the quantitative survey. To give a number, 72% of companies with formal programs of lean production are also data-driven, while only 35% of "non-lean" companies base their decisions on data. There are two explanations for the high correlation between data-driven decision-making and lean production. First, implementing lean means applying the scientific method in which workers continuously formulate hypotheses into the design of individual work activities, customer-supplier connection, production flow, and continuous improvement efforts (Spear & Bowen, 1999). An emblematic example is a Plan-Do-Check-Act tool. In the planning phase, workers formulate a hypothesis, transform them into improvement actions (do phase), test them in the check phase, and if supported, implement fully in the act phase. As Galileo Galilei noticed centuries ago, the hypothesis needs evidence and facts (i.e. data in this case) to be supported or rejected. Moreover, by formulating a hypothesis, workers are forced to think of formulating the right initial questions. Thus, a lean orientation at the firm may promote greater responsiveness to insights coming from data even these are collected manually from operators. Besides lean, another best practice to develop a data-driven vision is to start from management with analyzable and attainable objectives linked to operational efficiency, through which the data-driven vision will spread to the operators: "*It is clear that this shift requires time, but we hope that starting from the management this shift will then be embraced by the whole firm*".

9.2.1 From Uncertainty to Understanding capabilities through training, and analyzability with physical-digital interface technologies

Recent research suggests the investment into digital technologies can be useless, even harmful unless employees can incorporate data in complex decision-making processes (Shah et al., 2012). According to the VUCA framework, transformational skills are needed by all employees at different organizational levels (Millar, Groth, & Mahon, 2018). A data-driven philosophy must therefore be instilled at all levels, not only for top managers, industrial engineers, or data scientists. Managers cannot rely only on data talents, who are very difficult to find and costly to hire, but they should empower all employees to do their analytics work (Tudor & MacDonald, 2020). Indeed, data should be made available by investing in physical-digital interface technologies to increase the analyzability of events. Moreover, to exploit the "small data" collected by front-line workers daily (Lam, Sleep, Hennig-Thurau, Sridhar, & Saboo, 2017), they need to be involved as they own unique tacit knowledge and experience from the line (Susan Helper & Kuan, 2017). In this vein, training programs need to be put in place to provide front-line workers with basics of statistics, data literacy, analytical skills, and a "second-guess" attitude towards the outcomes of algorithms, needed to increase their understanding of phenomena to avoid automation bias and generate trust towards the use of data (Tudor & MacDonald, 2020). Again, lean environments can foster such involvement and upskilling of front-line workers' understanding.

9.2.3 From Complexity to Clarity in the supply-chain relationship with physical-digital interface technologies

Investing in physical-digital interface technologies can reduce the complexity of the relationship between suppliers and customers thanks to the traceability and virtualization properties. These properties increase the clarity and transparency of joint activities such as product development because the design activities occur within the shared virtualized object and because every activity in the design and manufacturing phases gets tracked which allow the partners to know the entire history of the product lifecycle (T. D. Hedberg et al., 2019). This will provide an improvement in the dyadic relationship in terms of trust in the relationship because every activity involved in the relationship gets tracked and virtualized.

9.2.4 From Ambiguity and Equivocality to Agility with network technologies

The "bottom-up" path, that of "connection", is an iterative stage in which an integrated data lake or data warehouse is introduced, and new digitization technologies are implemented by gradually connecting them and their data to such integrated IT infrastructure. As the "right-then-up" path is strongly suggested, the "up-then-right" path is strongly discouraged, i.e. investing in physical-digital interface technologies before changing from an intuition-driven to a data-driven mindset. If the firm has just digitized (i.e. Basic Digitalizer) and now wants to build a plant-wide digital twin and digital thread, it might be a waste of time and resources if a data-driven approach to decision making is not diffused first. Probably, the greater transparency could still provide some isolated process improvement opportunities (e.g. scrap reduction, reduction failures, and breakdowns) driven by technological improvements. However, unless employees incorporate a data-driven philosophy in their decision-making processes, the improvement opportunities remain isolated and short-term. On the other hand, the effectiveness of data-driven approaches will receive a boost thanks to the availability and reliability of big amounts of data throughout the plant. Events become less equivocal because data is ready for analysis (Pigni et al., 2016). With digitalized and integrated data in corporate information systems, where they are standardized and available for cross-function analyses, employees can perform better and heterogeneous data analysis. Cause-effect relationships are grounded in data coming from multiple sources, which allow explaining phenomena occurring in the manufacturing plant even beyond the expertise of middle managers.

Ensure Agility by collaborating with system integrators. Implementing network technologies represents a great technological challenge for manufacturing firms in terms of complexity, novelty, and customization as shown in section 6. To reduce the interpretative uncertainty, arising from these technological challenges, manufacturing firms have to collaborate with technological partners with relational governance practices based on co-creation and long-term collaboration. Among technological partners, system integrators represent a valuable partner due to their ability to provide one-stop-shopping solutions that range from network technologies implementation to data analytics solutions and process consulting. Co-creation allows the supplier to better know the specific needs and define better user requirements, with immediate benefit for a manufacturing firm in terms of clarity of its data flows. Long-term collaborations allow the development of trust, which is very relevant considering that as technological implementation unfolds the partners can provide data sharing-based consulting services. When collaborating with system integrators to implement network technologies, an agile approach focused on frequent interactions and delivery is strongly encouraged because it increases the overall user acceptance and supports the gradual reduction of interpretative uncertainty along with the development timespan (Gehrke et al., 2016)

Achieve Agility by fostering cross-functional collaboration. The access to a common and integrated pool of data is useless unless the organization has cross-functional collaboration practices among different departments such as teamwork, job rotation, face-to-face meetings, co-location, etc. Different streams of data have no value per se, and different units might not be aware of how and why these data should be combined. It is when functional knowledge is combined along with data that new improvement process opportunities arise. Cross-functional collaboration is an embedded practice of lean production and thus managers are highly encouraged to go under this development.

Achieve Agility by developing formal long-term collaborations with customers. Given that network technologies enable full and real-time transparency of process-related information, managers are encouraged to undertake a formal long-term relationship with their customers. These safeguarding mechanisms prevent that customers do not exploit such an integration opportunistically, since she can increase the visibility of suppliers' processes. Having relational norms and trust may not be sufficient but a formal and explicit shared commitment is also required.

9.3 Limitations and future research

This thesis presents some limitations which are avenues for future research. The main limitation of this thesis pertains to the generalizability of finding into other countries and industries. While the choice of a single country is a strength from a methodological point of view to keep fixed institutional factors and leave aside exogenous factors, it is also a weakness in terms of extension of the findings from Italy to other countries. Nevertheless, the result of this thesis may be extended to other advanced and industrialized countries, but careful considerations should be put when extending the findings in developing countries. A similar argument pertains to the extension of the research findings to other industries. While for similar capital-intensive industries such as the appliance industry result can be easily extended, careful considerations should be put for low capital-intensive industries in which organizational practices that in this thesis are considered as "best practices" may not be considered the same in these industries.

Concerning the findings of the digital properties, future research can use these to investigate the impact of digital technologies on other organizational practices and issues such as training, skills, privacy, control, etc. An interesting research area concerns the extent to which these digital properties allow new forms of control over employees' output that could lead us towards the era of "Surveilled Capitalism" (Zuboff, 2015).

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Appendix

Tables

Table A1. Commercial examples of network technologies

Technology provider	Network technology name	Reference
General Electric	Predix	ge.com/digital/iiot-platform
PTC	Kepware	kepware.com/
Reply	Brick Reply	reply.com/brick-reply
HighByte	HighByte Intelligence Hub	highbyte.com
Inductive Automation	Ignition	inductiveautomation.com/ignition
System Insights	Vimana	govimana.com/
Sight Machine	Factory Connect	sightmachine.com/

Table A2 Cluster Analysis

	Digitalizers (n = 41)	Networking Digitalizers (n = 6)	ANOVA
Data-Driven Decision-Making	0 (0)	0 (0)	F = n.a.
Physical-Digital Interface Technologies	2.71 (1.27)	4.00 (1.55)	F = 5.15*
Network Technologies	0 (0)	1.00 (0)	F = 52.58***
Cost Performance	0.15 (0.36)	0 (0)	F = 1.01

Note: Standard deviation in parentheses, $^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$

	Analytical Digitalizers (n = 33)	Smart Manufacturers (n = 5)	ANOVA
Data-Driven Decision-Making	1.00 (0)	1.00 (0)	F = n.a.
Physical-Digital Interface Technologies	3.82 (1.38)	3.80 (1.64)	F = 0.01
Network Technologies	0	1.00	F = 39.34***

	(0)	(0)	
	0.23	0.20	F = 0.02
	(0.36)	(0)	

Note: Standard deviation in parentheses, $^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$

Table A3. Measures of co-creation and continuous collaboration with system integrators

Construct	Measure	Operationalization
Co-creation	Indicate the role mainly played by the system integrator with regard to design and implementation of our automation and information systems? • We define the technical specifications and start the design phase, the system integrator completes the detailed project, develops the integration and builds the system (1) • We define our needs in principle, the system integrator defines the requirements, completes the detailed design, develops the integration and builds the system (2) • We use solutions proposed by the system integrator with a limited degree of customization (3)	Binary: value 1 if respondent answers (1), 0 otherwise
Continuous collaboration	Which of the following statements best identifies your relationship with the system integrator? • For each project we choose the system integrator that we consider most suitable (1) • There are few system integrators that we can refer to and alternatively we turn to them (2) • We typically have an ongoing relationship with a system integrator (3)	Binary: value 1 if respondent answers (3), 0 otherwise

Table A4. Factor analysis on types of tasks performed by production workers

Construct	Item	Factor 1	Factor 2	Ordinal Alpha
Autonomy in Equipment Management	Equipment Set-Up	-0.0023	**0.7568**	0.7357
	Modify Programs on Computerized Equipment	-0.1075	**0.5903**	

	Diagnose Equipment Problems	0.1412	**0.8176**	
	Inspect Work-In-Progress	**0.5037**	0.1281	
	Use Quality Data to Recommend Improvements	**0.7657**	0.0465	
Continuous Improvement	Meet with Customer Personnel	**0.5212**	-0.2676	0.6874
	Use a Computer	**0.6524**	0.1475	
	Each year we expect our shop workers to make substantial improvements in their own method of operations	**0.4290**	0.0110	

Figures

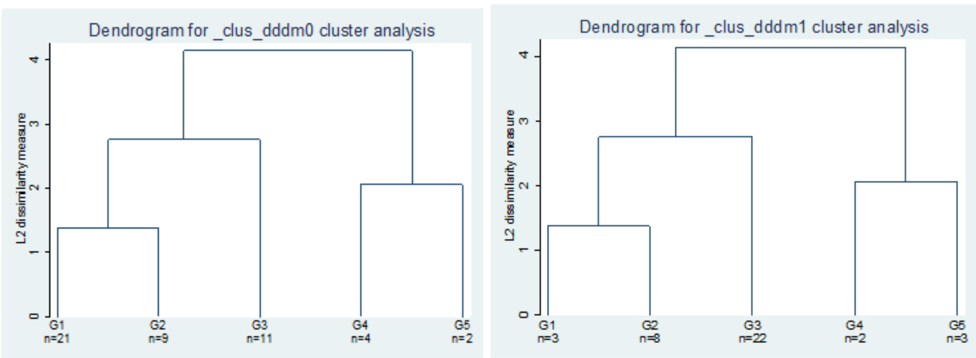

Figure A1. Dendrogram