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Adoption paths of digital transformation in manufacturing SME

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ABSTRACT

Digital transformation requires the implementation of different technologies that may improve the firms' capability in the collection, combination, processing, and use of business data. To guarantee an adequate combination of these technologies, several maturity models have been proposed in the literature, but only a few papers have investigated the actual implementation paths adopted by firms for digital transformation. In particular, no studies have investigated the implementation paths followed by SMEs, whose limited financial and human resources may prevent the adoption of the roadmaps developed for large firms. In this paper, we analyse the implementation paths for digital transformation adopted by a wide sample of Italian SMEs operating in different sectors. By combining Partial Least Squares Structural Equation Modelling with Necessity Condition Analysis, we clarify the specific enabler and enhancer roles played by different digital technologies. The study sheds further light on the relationship among these technologies and their contribution to the development of SMEs' information processing capability. In particular, our analysis shows that digital technologies associated with Industry 4.0 can be classified into four hierarchical layers, Sensor, Integration, Intelligence, and Response, that are in charge of the collection, combination, processing and use of organizational data. Our results show that the implementation of these layers is not based on a standalone approach since the lower layers enable and enhance the adoption of the upper layers. The present paper may also offer useful insights to managers and policymakers, interested in improving the digital transformation of SMEs.

1. Introduction

Digital transformation is widely recognized as a major technological revolution (Reischauer, 2018) that is giving start to a new economic paradigm, affecting industry structure, interactions with consumers' demand, and competition rules (Dalenogare et al., 2018; Reischauer, 2018). Indeed, digital transformation enables the implementation of the so-called Cyber-Physical System (CPS) in which the physical objects of the factory and the whole value network are integrated with information and communication technologies (Crnjac et al., 2017; Wang et al., 2016; Jeschke et al., 2017; Schwab, 2017). Differently from previous approaches to smart manufacturing, CPS can be implemented more flexibly, thus supporting the digitalization of firms characterized by specific requirements and operating in completely different environments and industries (Yu et al., 2015).

The implementation of CPS is mainly based on the adoption of advanced digital technologies, like those associated with the Industry 4.0 paradigm (Rüßmann et al., 2015). These technologies are characterized by a large heterogeneity not only because of their impact on different organizational functions (Gilchrist, 2016), from human resources management to new product development, logistics, manufacturing, and marketing, but also to their specific role in the firm's information processing. Indeed, some Industry 4.0 technologies, like the industrial Internet of Things and horizontal and vertical system integration, can improve the firm's capability to collect and integrate organizational data, while others, like smart manufacturing, can enhance the use of these data, promoting a more data-driven decision-making approach (Kuusisto, 2017) and increasing the precision and safety of the firm's operations (Vaidya et al., 2018). The combined adoption of these different technologies may promote full exploitation of the benefits of digital transformation since data collected and integrated by some technologies may satisfy the need for rich, reliable, and real-time data of other technologies (Vaidya et al., 2018). Thus, an effective combination of different digital technologies may sustain the

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development of the firm's information processing capability by creating the necessary physical infrastructure to deal with the operational uncertainty faced by the firm (Daft and Lengel, 1986).

As widely discussed by the Information Processing View (Galbraith, 1974) and Resource Based View (Aral and Weill, 2007; Tippins and Sohi, 2003), the firms can implement information processing capability by adopting and combining information systems, as well digital technologies associated with Industry 4.0 (Birkel and Hartmann, 2020; Ghobakhloo and Ching, 2019; Li et al., 2020; Somohano-Rodríguez et al., 2020), which can expand and leverage resources within the firm processes (Eller et al., 2020; Rivard et al., 2006; Wade and Hulland, 2004). Nevertheless, only a few papers extend their analysis to a plurality of technologies (Li et al., 2020; Somohano-Rodríguez et al., 2020), but they do not evaluate the paths of their implementation and combination, thus preventing the full understanding of their role in the development of the firm's information processing capability.

This lack may especially affect Small and Medium Enterprises (SMEs), whose limited financial, technological, and human resources may hinder the development of an effective adoption path of digital technologies, as well as the implementation of the same roadmaps used by large firms (Mittal et al., 2018). Besides, management literature has proposed only a few maturity models specifically targeted to SMEs (Mittal et al., 2018; Rafael et al., 2020), which are based on different critical dimensions, like the degree of implementation of specific technologies, without investigating the relationships among these dimensions.

This limitation of maturity models prevents from fully understanding the actual adoption paths of digital technologies in SMEs. As indicated by Frank et al. (2019), this topic remains an open question in the management literature, whose answer may benefit both researchers and practitioners interested in digital transformation. The present paper aims at partially filling this research gap by extending the analysis of the implementation patterns proposed by Frank et al. (2019) to the investigation of the adoption of digital technologies by SMEs.

While Frank et al. (2019) introduce a framework based on two layers of technologies (base and front-end technologies) according to their closeness to the final customers, the present paper develops a more complex model of implementation paths of digital transformation that highlights the role played by different technologies in the digital transformation of the SMEs. The proposed model classifies the related technologies into four hierarchical layers (Sensor, Integration, Intelligent, and Response), according to their role in the management of organizational data (Lu and Weng, 2018). As an example, data collected by a set of sensors applied to different raw materials, semi-finished products, and machines can be combined by horizontal and vertical system integration technologies and analysed in real-time by artificial intelligence algorithms, thus providing meaningful information to autonomous robots and other technologies directly involved in the production system (Moeuf et al., 2018). In general, the effectiveness of the technologies associated with the upper layers may depend on the output provided by the lower layers (Frank et al., 2019; Gillani et al., 2020). Nevertheless, the actual relationship among the technologies associated with different layers may be affected by the specific approach to digital technologies adopted by each firm. In this sense, the analysis of the actual implementation paths adopted by SMEs may clarify the enabler and enhancer role played by each technology involved in the digital transformation process.

To analyse the adoption paths of digital technologies, we carried out a survey involving 421 manufacturing SMEs from Tuscany, Italy, operating in different industries (mainly textile, machinery, furniture, paper, chemistry, jewellery). The survey is based on a questionnaire that investigates the maturity level of SMEs in terms of the adoption of several digital technologies. These data were analysed by two complementary approaches (Richter et al., 2020): Partial Least Squares Structural Equation Modelling (PLS-SEM) and Necessity Condition Analysis (NCA), that allow us to test if the implementation paths followed by SMEs in digital transformation are based on should-have (drivers) and must-have (bottlenecks) layers. Specifically, by computing a PLS-SEM model, we evaluate how much each layer of digital technologies contributes to the implementation degree of the technologies associated with the upper layers. Conversely, NCA allows us to test if the technologies associated with lower layers enable the implementation of the technologies associated with the upper layers.

The results of our PLS-SEM and NCA models may better explain the implementation paths of digital technologies by SMEs. Differently from the previous literature, we show how SMEs' digitalization depends on the combination of different technologies that may contribute to the effective management of organizational data. In particular, we highlight how digitalization is mainly enabled by Sensor technologies, which provide the necessary input for the proper functioning of the technologies associated with the upper layers. At the same time, Integration technologies seem to play a major enabler role for Intelligent and Response technologies, while Intelligent technologies appear to be still weakly combined with Response technologies.

These results shed further light on the implementation paths of digital transformation, extending the analysis carried out by Frank et al. (2019). First, the present study highlights the adoption paths of digital technologies by SMEs, thus filling a theoretical and managerial gap that may hinder the transformation of these firms. Second, the present study enriches the literature about the impact of digital technologies on the firm's information processing capability (Li et al., 2020; Somohano-Rodríguez et al., 2020), thanks to the adoption of a complex and systematic framework for the evaluation of the relationships between different digital technologies. Finally, the present study combines PLS-SEM and NCA, thus supporting a better understanding of the enabler and enhancer role played by different technologies. The complementarity between these methodologies, which has been jointly tested only in human resource management (Richter et al., 2021), may stimulate further applications in the management literature to better understand how technological phenomena are differently affected by some must-have and should-have factors.

The present paper may also provide several practical insights to practitioners, such as SME managers, interested in implementing digital technologies with a more systematic approach, as well as policymakers that aim at improving the degree of digitalization in SMEs by stimulating the use of more effective adoption patterns through appropriate policies or economic incentives.

The rest of the paper is organized as follows. Section 2 provides a review of the literature on the adoption paths of digital technologies in SMEs, supporting the formulation of several hypotheses based on must-have (bottlenecks) and should-have (drivers) factors. Section 3 describes our data and estimation model, whilst Section 4 shows the main results. Finally, Section 5 discusses the theoretical and practical contributions of the paper, its limitations, and possible future developments.

2. Literature review and hypotheses

2.1. The importance of an effective combination of different technologies for digital transformation

The management literature has widely discussed how digital transformation can sustain the firm's competitive advantage by supporting the development of more customer-oriented products and services (Martínez-Caro et al., 2020), strengthening the firm's collaboration network (Han and Trimi, 2022), and reducing costs and optimizing the use of time and other resources (Paolucci et al., 2021; Zangiacomi et al., 2020). The achievement of these benefits is made possible by the implementation of a set of different digital technologies, like those associated with Industry 4.0, such as the industrial Internet of Things, horizontal and vertical system integration, big data and analytics, and autonomous robots. While some of these technologies enable the collection of more reliable and heterogeneous data on the external and internal environment, others enhance a more effective and rapid integration, processing, and use of these data (Tao et al., 2018). The combination of these Industry 4.0 technologies provides the essential infrastructure for digital transformation and represents a necessary resource for the development of the firm's information processing capability, together with other complementary human and organizational resources (Kim et al., 2012; Tippins and Sohi, 2003).

In accordance with the Resource Based View, this infrastructure can be considered a resource, and not a simple asset, only if it is valuable, rare, difficult to imitate, and non-substitutable by other resources (Bharadwaj, 2000). In line with the analysis of the information systems by Wade and Hulland (2004) and Rivard et al. (2006), the infrastructure resulting from the implementation of Industry 4.0 technologies can be considered both valuable and non-substitutable since it can improve the firm's operations more than alternative existing technologies. The degree of rarity and inimitability of these technologies, at first sight, appears to be limited since they are usually purchased on the market, rather than internally developed by the firm (Lardo et al., 2020). Nevertheless, while the single Industry 4.0 technologies are available on the market, their implementation and combination should be accurately customized by considering the specific requirements, constraints, and capabilities of each firm (Mittal et al., 2018; Rauch et al., 2019). Hence, the need for a customized implementation may increase not only the degree of rarity of the infrastructure resulting from the combination of Industry 4.0 technologies, but also its inimitability since the information concerning the adoption path implemented by a firm cannot be easily accessible to external actors.

The impact of the infrastructure of Industry 4.0 technologies is mainly related to its role in the enhancement of the firm's information processing capability, which supports the collection, interpretation, and synthesis of relevant, accurate, and timely organizational data (Tushman and Nadler, 1978). As discussed by the Information Processing View (Galbraith, 1974), a firm can improve this capability by investing in information systems, which can more easily collect, transmit and process organizational data, thus guaranteeing a better fit with the information processing requirements (Tushman and Nadler, 1978). Information processing capability may be improved even by investing in Industry 4.0 technologies, as pointed out by previous studies that show how industrial Internet of Things (Birkel and Hartmann, 2020), cloud computing, big data and analytics (Li et al., 2020), cybersecurity, and robotics (Somohano-Rodríguez et al., 2020) can enable, in a peculiar way, more effective ways to collect, integrate, process or use organizational data. Nevertheless, to the best of our knowledge, the literature on the relationship between the firm's information processing capability and Industry 4.0 technologies is mainly focused on the analysis of a single technology (Birkel and Hartmann, 2020; Wu et al., 2013; Yu et al., 2021). The few papers that analyse more technologies (Ghobakhloo and Ching, 2019; Li et al., 2020; Somohano-Rodríguez et al., 2020) evaluate only the impact of their coexistence in the same firm, without considering how they are implemented and combined with each other.

Nevertheless, even if these technologies can be implemented on a standalone basis, the full exploitation of their functionalities can be achieved only through an appropriate combination (Ghobakhloo and Ching, 2019; Hofmann and Rüsch, 2017). Indeed, only the systematic implementation of these technologies, based on the connection of sensors and the sharing of interoperable data (Lu, 2017; Culot et al., 2020), enables the development of the firm's information processing capability. The relevance of an opportune combination between different Industry 4.0 technologies is pointed out also by Gillani et al. (2020), which highlight how the proper functioning of digital manufacturing technologies can be enabled only in presence of more basic technologies that provide the necessary inputs, in terms of digital and reliable data. Nevertheless, the combined implementation of different Industry 4.0 technologies requires the modernisation of production facilities with the harmonisation of their mechanical, electrical, and digital components, guaranteeing the standardization of communication protocols both at the intra-firm and the supply chain level (Kiel et al., 2017).

The need for a combined implementation of different Industry 4.0 technologies may especially hinder the digital transformation of SMEs (Horváth and Szabó, 2019; Masood and Sonntag, 2020). Indeed, the definition of an opportune combination of these technologies in SMEs can be prevented by their limited financial, material, and human resources, compared to those of large firms (Nguyen et al., 2015). Specifically, SMEs' capability to effectively combine new technologies in their production facilities can be crippled by the low experience in the use of Advanced Manufacturing Technologies by their human resources (Mittal et al., 2018). No wonder, management literature has devoted only limited attention to the implementation paths of these technologies by SMEs, with the proposal of a few maturity models specifically targeted to these firms (Mittal et al., 2018; Rafael et al., 2020). Nevertheless, these maturity models identify some different critical dimensions for the digital transformation of SMEs, as the degree of implementation of specific technologies, but they do not investigate the relationships among these dimensions. Hence, the analysis of the implementation and combination of different Industry 4.0 technologies in SMEs remains an open question, as recently highlighted by Frank et al. (2019) and Masood and Sonntag (2020).

To support the combination of Industry 4.0 technologies, it is necessary to understand the role of each technology in the whole digitalization of the firm. In this sense, several authors proposed different classifications that not only assign each technology to a specific layer, but also specify the relationships among different layers, thus emphasizing the importance of implementing technologies in an organized way. As an example, Frank et al. (2019) made a distinction between front-end technologies – which have an end-application purpose for the firm – and base-technologies – providing connectivity and intelligence to the first layer. Similar approaches have been proposed in some classifications of Internet of Things technologies (Aydos et al., 2019; Haghparast et al., 2021), which have been recently extended to the analysis of Industry 4.0 technologies by Lu and Weng (2018). In particular, the classification proposed by the latter authors is based on the role of each technology in the management of organizational data. They grouped Industry 4.0 technologies into four hierarchical layers: Sensor, Integration, Intelligent, and Response layers. The Sensor layer includes the sensors, monitoring and measurement technologies that scan the organizational environment and collect the related data. The Integration layer includes technologies that enable the integration of the data collected by the Sensor layer, which can be characterized by heterogeneous formats and structures (Davenport and Lucker, 2015). The Intelligent layer is based mainly on technologies for data processing that allow extracting knowledge and predictions from the data collected by the Sensor layer and/or merged by the Integration layer. Finally, the Response layer involves applications and services that use the data collected by the Sensor and Integration layers and the results of the computations made by the Intelligent layer, to improve organizational operations by automating some tasks and/or supporting the workforce. Table 1 presents a list of the main technologies associated with each layer.

The architecture proposed by Lu and Weng (2018) predicts a sequence of technology developments into a technology roadmap in which several development sequences are suggested (see Fig. 4 in Lu and Weng, 2018). Departing from Lu and Weng's architecture, we assume that the firm's information processing capability depends on the degree of implementation of the technologies associated with four hierarchical layers. Nonetheless, in describing the characteristics of these layers, they do not test how these technologies are combined with each other. We move from their classification to test how the adoption of technologies associated with lower layers may influence the implementation of technologies associated with upper layers.

In particular, we want to check both the "should-have" and the "must-have" relationships among technologies (Dul et al., 2010). In other terms, we are interested in understanding both whether a certain

Table 1
List of the main technologies associated with each layer.

Technological layer	Technology item
Sensor layer	Precision sensors; environment sensors; biometric sensors; RFID; module online monitoring; identification and measurement technology; vehicle tracking; digital data collection (including sales, production, purchasing).
Integration layer	Horizontal and vertical system integration (e.g. integration of machine tools, sensors, equipment, components, devices); industrial Internet of Things.
Intelligent layer	Big data analysis; artificial intelligence; analysis or forecasting of operational and market data.
Response layer	Decision making platform; enterprise resource planning (ERP); manufacturing execution system; production scheduling optimization; simulation systems; autonomous robots; smart manufacturing factory; collaborative planning, forecasting and replenishment integrated system; supply chain collaboration software; warehouse management systems.

Source: adapted from Lu and Weng (2018).

layer can act as a contributing factor for successive layers ("should-have" technologies) and as an enabling factor for successive layers ("must-have" technologies). In the first case, the higher the intensity with which technologies in one layer are adopted, the higher will be the possibility to exploit technologies belonging to successive layers of the framework. In the latter case, instead, the technologies of one layer are necessary conditions, meaning that if they are not implemented at a given level, it will not be possible for the firm to adopt some levels of technologies belonging to successive layers (necessity logic). To better understand the relationship between lower and upper layers, in the following sections we discuss in detail how this relationship can be interpreted following contributing and necessity logics.

2.2. Lower layers as contributing factors for upper layers

Sensor technologies support the process of gathering new data from the organizational context: to guarantee correct and reliable data, it is important to adequately select the sources and devices through which data can be collected (Lu and Weng, 2018; Xu and Duan, 2019). Sensor technologies are often embedded in machines thanks to Programmable Logic Controllers (PLC), which allows the continuous collection of data related to all the stages of the manufacturing process. All these data are valuable sources that the firm can apply to improve product quality, reduce defectiveness, and increase its flexibility and productivity. The adoption of Sensor technologies may enhance not only the firm's capability to collect and record organizational data, but may also its capability to transform these data into knowledge and develop new operational solutions. Indeed, the availability of a larger volume and variety of data coming from all over the firm may increase the firm's propensity to implement technologies that guarantee a correct combination, processing, and use of these data (Matt and Rauch, 2020).

In particular, an increase in the level of adoption of Sensor technologies may positively affect the degree of adoption of Integration technologies. Indeed, in a firm that has adopted digital transformation, data generally come from various sources, which can be also dramatically different. Data collected through Sensor technologies remain, though, only isolated facts, sets of discrete events that have, by themselves, no meaning (Davenport and Prusak, 1998), unless they are combined by Integration technologies. For example, the combination and integration of virtual and physical worlds provide data in a new way, which allows collecting real-time information on production processes (Matt and Rauch, 2020; Rauch et al., 2019). For these reasons, we posit that:

H1a. A higher degree of adoption of Sensor layer technologies positively affects the degree of adoption of Integration layer technologies.

Data coming from sensors can be also used by the Intelligent layer technologies. In particular, big data and analytics strongly rely on a large and varied amount of data to uncover hidden paths, unknown correlations, market trends, and customer preferences (Martinelli et al., 2021). As an example, Baek and Kim (2019) show how big data and analytics can improve the detection of fault paths by using data collected by a large variety of sensors. From this perspective, a large amount of data collected may increase the firm's propensity to adopt technologies that can efficiently process these data, like those associated with the Intelligent layer. For these reasons, we posit that:

H1b. A higher degree of adoption of Sensor layer technologies positively affects the degree of adoption of Intelligent layer technologies.

Finally, sensors collect and pass data also to the highest layer of technologies, Response one, which includes robots and other technologies that can either support human resources in the firm's operations or autonomously carry out them. The propensity to adopt Response technologies, which takes as inputs configuration and process data (Rojas and Ruiz Garcia, 2020), may be positively affected by the firm's capability to collect larger and richer data. As an example, additional data provided by Sensor technologies can provide a more precise and reliable picture of the factory, thus supporting a more advanced use of Warehouse Management Systems (Zhang et al., 2021). For these reasons, we posit that:

H1c. A higher degree of adoption of Sensor layer technologies positively affects the degree of adoption of Response layer technologies.

Sensor technologies are characterized by a large variety, from RFID, machines and sensors, camera images, to social media (Gröger, 2018; Jiang et al., 2016). For this reason, they may be characterized by heterogeneous formats and structures (Davenport and Lucker, 2015). Nevertheless, putting together all these data can provide new information on the manufacturing processes, since their integration at a global level can get a new "meaning" for the firm. At this aim, the Integration layer includes technologies that perform the cleansing, combination and historicization of data collected by the Sensor layer (Gröger, 2018). In this sense, the selection of the most appropriate Integration technologies can guarantee an opportune level of data accuracy, redundancy, and consistency (Xu and Duan, 2019).

How data are integrated is crucial for big data and analytics, which are essential technologies of the Intelligent layer. Indeed, the implementation of big data and analytics may be enhanced not only by the availability of a larger volume of data provided by Sensor technologies, but even by the larger adoption of Integration technologies that guarantee a more advanced standardization and combination of these data. For example, Dremel et al. (2017) showed how the implementation of more advanced big data analytics, which allow also predictive analysis, was funded by large investments in Integration technologies. For these reasons, we posit that:

H2a. A higher degree of adoption of Integration layer technologies positively affects the degree of adoption of Intelligent layer technologies.

A higher degree of adoption of the Integration layer may also improve the development of technologies associated with the Response layer. Indeed, the adoption of the Integration layer may affect the quantity and quality of information passed to the Response layer, and, as a consequence, the possibility to exploit knowledge and develop more advanced solutions based on the use of these data. In this sense, Kritzinger et al. (2018) discussed how the implementation of Integration technologies that combine digital and physical objects more systematically way allows the adoption of more advanced tools for the simulation and optimization of the firm's operations. Therefore, we posit that:

H2b. A higher degree of adoption of Integration layer technologies positively affects the degree of adoption of Response layer technologies.

The Intelligent layer is mainly based on technologies for data processing, such as big data and analytics, and, more generally, artificial intelligence. These technologies allow extracting knowledge and predictions that cannot be directly drawn forth from the data collected by the Sensor layer and/or combined by the Integration layer. In particular, these technologies can provide knowledge through descriptive, diagnostic, predictive, and prescriptive analytics, the latter focusing on optimization (Gröger, 2018) and being the input to the Response layer, which may develop applications and services. As an example, artificial intelligence based on advanced analytical tools can monitor and forecast many aspects of production, from machine failures to overloads and product nonconformities, reducing costs and increasing productivity (Frank et al., 2019). In some cases, outputs of Intelligent layer technologies can support the implementation of advanced Response technologies, like self-organizing systems, able to react to different scenarios. As an example, products and machines in a production system could be able to jointly interact and push the system to a self-configuration and self-optimization (Zsifkovits et al., 2020). For this reason, we posit that:

H3. A higher degree of adoption of Intelligent layer technologies positively affects the degree of adoption of Response layer technologies.

2.3. Lower layers as necessary factors for upper layers

In the previous section, we discussed how a higher degree of implementation of technologies associated with a lower layer may stimulate a more advanced adoption of technologies associated with the upper layers. In this view, the technologies associated with lower layers are considered as enhancers (should-have factors) of the firm's information processing capability since they may support a superior integration, processing, and use of organizational data, thanks to a higher degree of implementation of the technologies associated with upper layers. In this section, we discuss how the technologies associated with the upper layers cannot be properly implemented without the adoption of technologies associated with lower layers, thus considering these latter as enablers (must-have factors) of the firm's information processing capability.

According to Schütze et al. (2018), the adoption of Sensor technologies is a prerequisite for the generation of new organizational knowledge, thus enabling more advanced digital technologies and many authors have considered sensors technologies as crucial enablers of digital transformation (Frank et al., 2019; Matt and Rauch, 2020). Indeed, the huge volume of organizational data generated by sensors becomes the input for Integration, Intelligent and Response technologies that may use them to gather information and knowledge and to develop new solutions.

More specifically, since the technologies associated with the Integration layer are in charge of data cleansing, combination and historicization (Gröger, 2018), their adoption is motivated only by the presence of Sensor layer technologies that collect data characterized by a certain variety, in terms of formats and structures. For example, the implementation of a large variety of sensors by different actors in the supply chain has made it necessary to adopt technologies that can guarantee a sufficient degree of standardization and interoperability of operational data (Gölzer and Fritzsche, 2017). For this reason, we posit that:

H4a. The adoption of Sensor layer technologies is a necessary condition for the adoption of Integration layer technologies.

Similarly, the implementation of technologies associated with the Intelligent layer, especially big data and analytics, is motivated by the need to process the huge volume of data made available by Sensor technologies. In this sense, the interdependence between Sensor and Intelligent technologies requires that the implementation of Internet of Things solutions must be combined with the adoption of big data and analytics that make it possible to process the huge volume of data gathered by these sensors (Addo-Tenkorang and Helo, 2016). For this reason, we posit that:

H4b. The adoption of Sensor layer technologies is a necessary condition for the adoption of Intelligent layer technologies.

Finally, Sensor technologies may represent an enabler even for technologies associated with the Response layer, since this latter can properly work only if supported by a continuous flow of reliable operational data. For example, the implementation of robots operating in warehouse management must be supported by real-time data collected by laser sensors (Zhang et al., 2021). Even the full implementation of ERP systems needs the collection of the real-time updates of the production system that can be guaranteed only by adequate sensors (Mittal et al., 2020). For this reason, we posit that:

H4c. The adoption of Sensor layer technologies is a necessary condition for the adoption of Response layer technologies.

Integration technologies are recognized as enablers for digital transformation (Matt and Rauch, 2020; Rauch et al., 2019) since their role in the conversion of organizational data into information is essential for the development of a CPS (Lee et al., 2013). Indeed, the great variety of Sensor technologies makes it necessary to standardize and combine the collected data before their processing and use.

In particular, the implementation of Intelligent technologies, like big data and analytics, imposes a critical challenge that is related to the intrinsic complexity of the organizational data collected through a myriad of sources (Gandomi and Haider, 2015). This challenge can be solved by the implementation of Integration technologies that can combine different data not only along with the levels of the automation pyramid, but also along the life cycle of the CPS, the whole value chain and the value network (Gölzer and Fritzsche, 2017). Therefore, we posit that:

H5a. The adoption of Integration layer technologies is a necessary condition for the adoption of Intelligent layer technologies

Integration technologies are also essential for the implementation of technologies, like those associated with the Response layer, that use the organizational data for supporting or automatizing operations. In this sense, the adoption of Internet of Things, which guarantees not only the integration between the different physical equipment in the shop floor, but also the development of a whole digital twin, enables the implementation of Response technologies, like simulations, which need a complete and up-to-date view of the factory (Borangiu et al., 2019). Therefore, we posit that:

H5b. The adoption of Integration layer technologies is a necessary condition for the adoption of Response layer technologies

The Intelligent layer takes information from the Integration and Sensor layers and uses value-added analytics to generate insights and suggested actions. The technologies associated with the Intelligent layer supports the creation of new knowledge through the contextualization of the collected and combined data in a background of already existing organizational knowledge. Indeed, according to Wang et al. (2016), Intelligent technologies, like data analytics or artificial intelligence, can provide global feedback and coordination to the smart factory.

The results of data processing activities are a necessary input for the technologies associated with the Response layer, which can take advantage of artificial intelligence to solve operational problems and improve the customer experience. Indeed, data analytics can make sense of all data coming from the Integration and Sensor layers, thus supporting decision-making on a real-time basis (Chen et al., 2015). For example, the use of data analytics is essential for the implementation of Response technologies that aim at optimizing the process parameters of smart manufacturing systems and shop floors (My, 2021). Therefore, we posit that:

H6. The adoption of Intelligent layer technologies is a necessary condition for the adoption of Response layer technologies.

Fig. 1 summarizes all the hypotheses discussed and tested in the paper.

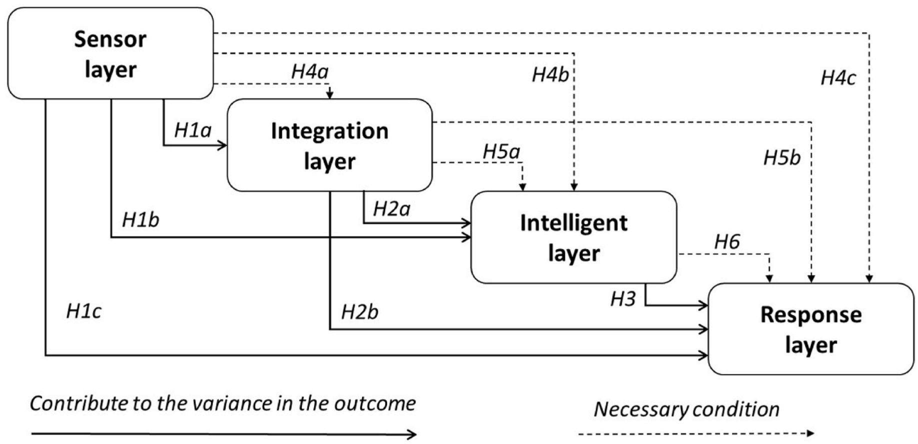

Fig. 1. Summary of the hypotheses.

3. Data and method

In order to explore how SMEs implement the digital transformation, we administered a survey to collect data on a large sample of SMEs located in Tuscany, Italy. By using these data, we have defined indicators of the implementation degree of the technologies associated with the four layers described by Lu and Weng (2018). Finally, we have adopted PLS-SEM and NCA to test our hypotheses.

3.1. Sample and survey method

To collect data concerning the degree of implementation of digital transformation by SMEs, we administered a detailed survey, funded by the Tuscany Region and carried out by researchers of the Universities of Florence, Pisa and Siena (Casprini and Zanni, 2020). The survey was administered in the period from July 2018 to October 2019.

The questionnaire consisted of several closed-ended 5-point scale items according to the level of SME adoption of the various digital technologies under analysis. The items, which are presented in Appendix A, were developed by an expert panel and pre-tested on a limited sample of SMEs to check face validity.

The sectors involved in the research were specified by the Regional Government among those most related to the industrial districts or traditional sectors in Tuscany, in the centre of Italy. According to the Standard Industrial Classification (SIC), they included: Apparel and other finished products made from fabrics and similar materials; Chemicals and allied products; Industrial and commercial machinery and computer equipment; Jewellery, silverware, and plated ware; Paper and allied products; Ship and boat building and repairing, furniture and fixtures. Despite the high value-added of these local industries, Tuscany resulted as the Italian region with the lowest presence of firms with an advanced implementation of Industry 4.0 technologies (MISE, 2018). Table 2 reports the sectorial distribution of the firms in the sample, as well as their size and age. As shown in this table, most firms in the sample are small enterprises with an age between 10 and 50 years.

To be sure that firms had the capabilities to invest in digital transformation, we considered only SMEs with a positive economic performance in the last three years. The sampling frame was composed of 2741 SMEs, all of which were contacted via e-mail and telephone to check their availability to answer a questionnaire. The survey was administered by expert interviewers with multi-year experience in management issues, who visited the SME and filled in the questionnaire, by discussing the questions with a manager (usually, the CEO or the Production director) and by checking the results through direct observation of the production facilities. The answers were recorded in a database accessible via web, which allowed us to avoid missing data. The presence of expert interviewers alleviated face validity, since their clarifications favoured a more homogeneous interpretation of the items by the respondents. Besides, the presence of the interviewer may reduce the impact of common method bias, since her/his clarification may improve the interpretation of scale items and her/his observation may validate, or challenge, the answers provided by the respondents (Podsakoff et al., 2003). To further decrease the possible common method bias, items associated with the different layers were presented on different sections of the questionnaire, thus preventing the respondents from identifying any relationship among the constructs. Potential common method bias is also evaluated in the post-hoc analyses in section 4.3.

Table 2
Characteristics of the sample.

Sector	%
Apparel and other finished products made from fabrics and similar materials	51
Chemicals and allied products	5
Industrial and commercial machinery and computer equipment	23
Jewellery, silverware, and plated ware	5
Paper and allied products	5
Ship and boat building and repairing; furniture and fixtures	11
Size	**%**
Microenterprise (≤10 employees)	22
Small enterprise (≤50 employees)	61
Medium enterprise (≤250 employees)	17
Age	**%**
≤10 years	14
≤50 years	81
≤90 years	5

To evaluate potential non-response bias, we computed the difference between early and late respondents. A *t*-test of difference was performed on the number of employees and on the four constructs. The *t*-test for early and late responses had a p-value = 0.102 (t = 1.653) for the number of employees, a p-value = 0.321 (t = 0.999) for the Sensor, a p-value = 0.241 (t = 1.182) for Integration, a p-value = 0.804 (t = 0.248) for Intelligent, a p-value = 0.3577 (t = 0.925) for Response. The high p-values associated with these differences suggest that the response time does not significantly affect the answers provided by SMEs.

In total, we collected 421 completed responses to the questionnaire, thus reaching a response rate equal to 15.36%.

3.2. Measurement of industry 4.0 technologies

Every single item of our questionnaire assesses the adoption of a specific technology that can deploy a peculiar, not interchangeable function in the management of the organizational data. To measure the degree of implementation of digital transformation, we have assigned these items to each of the four layers described by Lu and Weng (2018): Sensor, Integration, Intelligent, and Response layers. In particular, items associated with technologies for data collection are assigned to the Sensor layer, those for data combination to the Integration layer, those for data processing to the Intelligent layer, and those for data use to the Response layer.

To have a more complete view of the degree of implementation of these technologies we have adopted a large number of items in our questionnaire. Specifically, the implementation of the Sensor layer has been measured by 12 items, the Integration layer by 9 items, the Intelligent layer by 7 items, and the Response layer by 12 items.

We measured the implementation of the technologies associated with these four layers by using formative indexes. The causal-formative measurement model assumes that the observed indicators cause the latent variable: an error term is included in the equation to capture the remaining causes not represented by the indicators (Benitez et al., 2020). An omission of causal indicators may lead to biased parameter estimates of the causal indicators, but Aguirre-Urreta et al. (2016) showed that the meaning of the latent variable is not affected by omitting causal indicators and the remaining model parameters can be consistently estimated. Hence, each causal-formative indicator measures the degree of implementation of the different technologies associated with each layer.

3.3. Computational method

Following Richter et al. (2020), we evaluated if the layers of Industry 4.0 technologies are linked with each other by both must-have and should-have factors, by using, respectively, NCA and PLS-SEM. In particular, we combined these complementary methods that allow us to test if a lower layer enables and leads to a higher value of an upper layer (Richter et al., 2021).

First, to assess if the technologies associated with the lower layers lead to a higher degree of the technologies associated with the upper layers, we used PLS-SEM, which is a structural equation modelling technique based on path and regression analysis (Hair et al., 2017). As discussed by Hair et al. (2017), PLS-SEM is suitable for testing causal relationships among latent variables (technological layers) and it can deal with the model constructs and measurement items simultaneously. This means that causal explanations, according to a counterfactual view of causality, are tested, and a measure of predictive accuracy is also obtained, which should yield meaningful managerial implications. PLS-SEM identifies the contribution to the variance in the outcome, that takes the form “X has a positive effect on Y” (Richter et al., 2021). Then, it is possible to estimate the “should-have” factors for technology development. Moreover, PLS-SEM is not sensitive to the characteristics of the distribution of variables. In this research, a formative measurement model has been used: as a consequence, the variables, called manifest variables, reflect one-dimensional latent constructs (Hair et al., 2017). We used R with the package cSEM to estimate PLS-SEM with 5000 bootstrap replications (Rademaker and Schuberth, 2020). Mode B (path weighting scheme) was selected for the formative-measured indicators.

Second, we adopted NCA (Dul, 2016) to assess if the technologies associated with the lower layers are must-have factors for the technologies associated with the upper layers. If so, the absence of technologies associated with the lower layers cannot be compensated for by other factors, thus preventing the implementation of technologies associated with the upper layers. To evaluate the necessary conditions between the technologies associated with the four layers analysed in our study, we performed an NCA on the latent variable scores associated with every layer and computed by PLS-SEM. By using the R package NCA (Dul, 2018), we estimated the effect size and its significance level of each necessity condition discussed in our hypotheses, considering a ceiling line computed by using both the ceiling envelopment and the ceiling regression with free disposal hull, and 10,000 permutations to estimate the significance levels (Dul, 2020).

4. Results

By applying both NCA and PLS-SEM, we tested our hypotheses, thus clarifying the relationships between the technologies associated with the four layers under analysis.

4.1. PLS-SEM results

Formative measures and the structural model were validated following the last available guidelines for PLS-SEM (Hair et al., 2017, 2019, 2020). In particular, we tested our formative measurement models for convergent validity, indicator multicollinearity, size and significance of indicator weights, by using Confirmatory Composite Analysis (Hair et al., 2020).

Convergent validity was based on the size of the path coefficient between the formative construct and a reflective measure that was included in the questionnaire. All four measures showed a minimum path coefficient of 0.7, confirming convergent validity (Hair et al., 2017, 2020). To assess if indicator multicollinearity is a problem, the variance inflation factor (VIF) was examined, see Table 3. All VIFs are below 3.0, so multicollinearity is not a problem. The size and significance of the indicator weights are reported in Table 3: larger significant weights are more relevant. In such a case, there is not a suggested threshold because when the number of indicators increases, it is likely that more indicators have low weights. In our case, all the indicator weights are statistically

Table 3
Formative measurement.

Construct	Items	VIF	Weights	Significance level	Loadings
Sensor	Sensor01	1.268	0.111	**	0.368
	Sensor02	1.531	0.130	**	0.565
	Sensor03	1.606	0.301	***	0.668
	Sensor04	1.457	0.161	**	0.491
	Sensor05	1.111	0.144	***	0.362
	Sensor06	1.142	0.097	*	0.222
	Sensor07	1.290	0.124	**	0.481
	Sensor08	1.270	0.199	***	0.444
	Sensor09	1.210	0.151	***	0.372
	Sensor10	1.268	0.272	***	0.617
	Sensor11	2.299	0.169	**	0.617
	Sensor12	2.150	0.102	*	0.543
Integration	Integ01	1.289	0.351	***	0.700
	Integ02	1.249	0.149	***	0.527
	Integ03	1.209	0.090	**	0.434
	Integ04	1.571	0.342	***	0.776
	Integ05	1.232	0.159	***	0.382
	Integ06	1.233	0.216	***	0.492
	Integ07	1.677	0.129	**	0.577
	Integ08	1.356	0.122	**	0.471
	Integ09	1.749	0.127	**	0.571
Intelligent	Intel01	1.410	0.403	***	0.782
	Intel02	1.402	0.115	**	0.523
	Intel03	1.619	0.189	***	0.698
	Intel04	1.460	0.214	***	0.665
	Intel05	1.336	0.085	*	0.506
	Intel06	1.523	0.351	***	0.782
	Intel07	1.267	0.086	*	0.388
Response	Resp01	1.296	0.057	*	0.461
	Resp02	1.567	0.150	***	0.659
	Resp03	1.636	0.177	***	0.674
	Resp04	1.666	0.174	***	0.707
	Resp05	1.636	0.239	***	0.746
	Resp06	1.070	0.097	**	0.245
	Resp07	1.260	0.134	***	0.534
	Resp08	1.440	0.064	**	0.517
	Resp09	1.791	0.130	***	0.676
	Resp10	1.690	0.131	**	0.676
	Resp11	1.369	0.069	**	0.483
	Resp12	1.818	0.161	***	0.725

Significance level: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Table 4
Structural model collinearity (VIF).

	Sensor	Integration	Intelligent
Intelligent	2.328	2.328	
Response	2.710	3.091	2.960

significant at a 5% level using bootstrapping.

To validate the structural model, we followed the last available guidelines (Hair et al., 2017, 2019, 2020). Multicollinearity in the structural model was examined by computing VIFs between constructs, see Table 4. As for formative indicators, the suggested level is below 3.0, and in our case, this criterion is fully met except in one case which is very close to the threshold (3.091). We considered this result good given its proximity to the threshold. Table B.1 (Appendix B) shows the correlation matrix of constructs.

Fig. 2 and Table 5 show the results of the structural model for the entire sample. Bootstrap validation with 5000 resamples has been used. The analysis shows that the Sensor layer is a significant predictor for the Integration (H1a is confirmed), the Intelligent (H1b is confirmed), and the Response layers (H1c is confirmed), whilst the Integration layer positively affects the Intelligent layer (H2a is confirmed) and the Response layer (thus, H2b is confirmed). Finally, also H3 is confirmed: a higher degree of implementation of the Intelligent layer positively affects the degree of adoption of the Response layer.

To further analyse the structural model in Table 5 we show the explained variance (R^2) of the endogenous constructs. R^2 is frequently used to assess the structural model in PLS-SEM models that aim at maximizing the variance explained in the endogenous variables. In our analysis, all the values of R^2 are between 0.570 and 0.845 and they are considered from moderate to substantial concerning the explanatory power of the model (Hair et al., 2019). To evaluate the effect size of each predictor, we have considered the Cohen f^2 indicator (Cohen, 1988; Hair et al., 2020): this index is given by the increase in R^2 compared with the proportion of variance that remains unexplained in the endogenous latent variable, providing an estimate of the predictive ability of each independent variable.

Table 5 shows that the effect sizes of the Sensor on the Integration layer and of the Integration on the Intelligent and the Response layers can be considered large (Cohen, 1988; Hair et al., 2020). Moreover, the effect of the Sensor on the Response and Intelligent layers can be considered as medium effects. Indeed, according to Cohen (1988) and Hair et al. (2020) the cut off values of f^2 for large and medium effects are 0.35 and 0.15, respectively. Finally, according to our model, the Sensor layer influences the Intelligent and Response layers also indirectly and it is possible to compute the total effects as shown in Table 5.

4.2. NCA results

The results of NCA applied to latent variable scores associated with every layer and computed by PLS-SEM are presented in Table 6. The first half of the table presents the results obtained by applying the ceiling envelopment with free disposal hull (CE-FDH), while the second half the results obtained by applying the ceiling regression with free disposal hull (CR-FDH). These two different approaches show consistent results, thus confirming the robustness of our analysis. Each cell presents the value of the effect size of a lower layer, indicated in the row, on the upper layers, indicated in the column. The effect size measures the degree to which a necessity condition between a lower layer and an upper layer is confirmed. In particular, following Dul (2020), an effect size $d < 0.1$ represents a small effect, $0.1 \leq d < 0.3$ a medium effect, $0.3 \leq d < 0.5$ a large effect, while $d \geq 0.5$ a very large effect. Thus, our results show that the Sensor layer is a large enabler for all the upper layers. The Integration layer seems to be a medium enabler for both the Intelligent

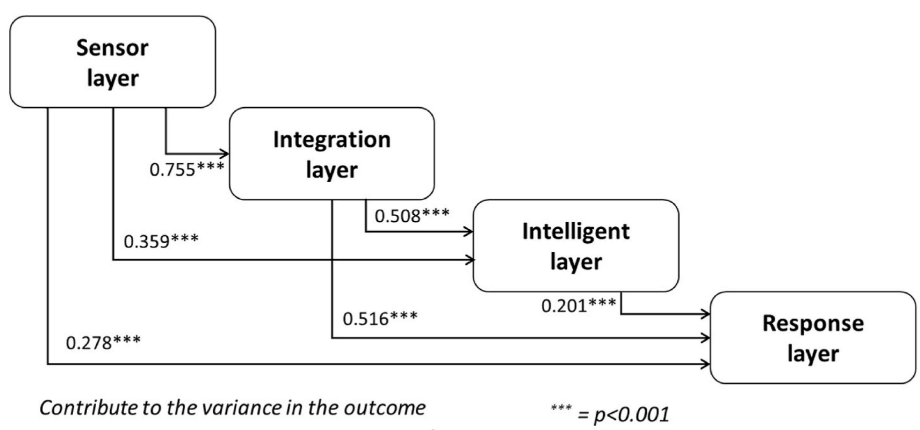

Fig. 2. Results of the structural model estimation (*** = p < 0.001).

Table 5
Estimation of the structural model – Contribute to the variance in the outcome.

Relationship	Direct effect		Indirect effect		Total effect				Hypothesis
	β	P	β	p	β	p	f^2	R^2	
Effect on Integration								0.570	
Sensor	0.755	<0.001			0.755	<0.001	1.328		*H1a*
Effect on Intelligent								0.662	
Sensor	0.359	<0.001	0.383	<0.001	0.743	<0.001	0.164		*H1b*
Integration	0.508	<0.001			0.508	<0.001	0.328		*H2a*
Effect on Response								0.845	
Sensor	0.278	<0.001	0.539	<0.001	0.817	<0.001	0.184		*H1c*
Integration	0.516	<0.001	0.102	<0.001	0.618	<0.001	0.555		*H2b*
Intelligent	0.201	<0.001			0.201	<0.001	0.088		*H3*

Table 6
Effect size of the necessary conditions between the technologies associated with the four layers.

CE-FDH	Integration layer	Intelligent layer	Response layer
Sensor layer	0.433***	0.337***	0.439***
Integration layer	–	0.220***	0.263***
Intelligent layer	–	–	0.314***
CR-FDH	**Integration layer**	**Intelligent layer**	**Response layer**
Sensor layer	0.411***	0.313***	0.420***
Integration layer	–	0.201***	0.236***
Intelligent layer	–	–	0.312***

Significance level: *p < 0.05; **p < 0.01; ***p < 0.001.

and the Response layer. Finally, the Intelligent layer is a large enabler for the Response layer. In sum, NCA shows how the Sensor layer represents enabling technologies for those included in all the upper layers, thus supporting *H4a*, *H4b*, and *H4c*. The technologies associated with the Response layer are further enabled by the Intelligent layer, in line with *H6*. Only the Integration layer shows a smaller effect on both the Intelligent and the Response layers, thus supporting *H5a* and *H5b*, even if with medium effects. This result seems to indicate that the technologies for data processing and use often are based on data collected by homogeneous sources that do not require to be combined by technologies associated with the Integration layer.

Appendix C contains both scatter plots and bottleneck tables of the computed NCAs. Specifically, scatter plots show the values of the dependent and independent layers under analysis for each SME, together with the CE-FDH and CR-FDH ceiling lines and the OLS regression line, which is used as a reference. Bottleneck tables present the necessary level of the dependent layer for several given levels of the dependent layer. For example, Table C.1 shows that to reach the highest observed value of the Integration layer (100%), it's necessary to have at least a value equal to 87.9% of the observed interval of the Sensor layer, in the case of CE-FDH (82.6% in case of CR-FDH).

4.3. Post-hoc analyses and robustness check

In this section, we test the robustness of structural model parameters by extending the model or running complementary methods. In particular, we checked common method bias, endogeneity, and unobserved heterogeneity because they can pose serious threats to the results' validity (Sarstedt et al., 2020).

To detect possible common method bias, two statistical techniques have been employed (Fuller et al., 2016; Narayanan et al., 2021; Kim et al., 2019). First, in line with Harman's single-factor test, we carried out a principal component analysis with the unrotated solution. The results show that the general factor accounts for 27% of the total variance of the measures. This result is the first indication that the substantial variance by the common method is not a serious concern in the current study. Second, the full collinearity of the PLS-SEM model, reported in Table 4, indicates that the model is free from common method bias because all the variance inflation factors (2.328≤ VIF ≤3.091) are less than the criterion values (3.3) suggested by Kock (2015). All these results suggest that common method bias is not a serious concern in the current analysis.

Endogeneity may result from simultaneous causality, omitted variables or measurement errors. Following Hult et al. (2018) and Sarstedt et al. (2020), we adopted the Gaussian copula approach (Park and Gupta, 2012), which does not require instrumental variables to be specified. This controls for endogeneity by directly modelling the correlation between the endogenous variable and the error term by means of a copula. The latent variable scores of the original model estimation are used as input. We tested six regression models (1, 3, 4, 9, 10, 11) in which each independent construct is considered as possibly exhibiting endogeneity. In addition, to simultaneously account for multiple endogenous variables, we tested five further regression models (2, 5, 6, 7, 8) that include all the possible combinations of multiple endogenous variables in our path model. The results in Table B.2 show that some of the copulas are significant (p < 0.05). In particular, Integration copula is significant in all the models (p < 0.05), which points to a potential endogeneity issue. For example, the effect of Integration on Response, in model 10, changes from 0.516 to 0.719. Conversely, Sensor copula is significant only in model 1, where the estimated effect of Sensor on Integration changes from 0.755 to 1.636. Finally, Intelligent copula is never significant. In sum, neither changes of sign nor losses of significance are found in all the models. To summarize, endogeneity cannot be eliminated in our study, but it does not affect our results substantially.

Heterogeneity has been investigated by checking how both SME sectors and their size affect the path estimates of the PLS-SEM structural model. Since the limited numerosity of some sectors in our sample, we aggregated them by their technological similarity. Thus, we joined into Sector A both Jewellery, silverware, and plated ware and Apparel and other finished products made from fabrics and similar materials, while Sector B includes only Industrial and commercial machinery and computer equipment, and Sector C includes all the other sectors. We applied the test proposed by Chin and Dibbern's (2010), using 2000 permutations. The results of this test in Table 7 show that the path coefficient estimates are almost invariant across sectors of the sample since there is just one significant difference out of 18 pairwise comparisons in the path estimates of PLS-SEM.

By using the same approach, we compared the path coefficients of the PLS-SEM models by considering three classes of SMEs, i.e. medium, small, and micro-enterprises. The results of this test in Table 8 show that the path coefficient estimates are almost invariant across size since there is no significant difference out of 18 pairwise comparisons in the path

Table 7
Estimation of the PLS-SEM structural model by sectors.

Relationship	Sector A)	Sector B)	Sector C)	Difference A)-B)	Difference A)-C)	Difference B)–C)
	Β	β	β			
Effect on Integration						
Sensor	0.785***	0.726***	0.695***	0.059	0.090	0.031
Effect on Intelligent						
Sensor	0.447***	0.264**	0.403**	0.183	0.044	−0.139
Integration	0.433***	0.639***	0.512***	−0.206	−0.079	0.127
Effect on Response						
Sensor	0.286***	0.186*	0.333**	0.101	−0.046	−0.147
Integration	0.549***	0.387**	0.308*	0.162	0.242	0.080
Intelligent	0.149*	0.426***	0.367**	−0.278*	−0.218	0.059

Note: A) Apparel and other finished products made from fabrics and similar materials; Jewellery, silverware, and plated ware; B) Industrial and commercial machinery and computer equipment; C) Chemicals and allied products; Paper and allied products; Ship and boat building and repairing; Furniture and fixtures. Significance level: *p < 0.05; **p < 0.01; ***p < 0.001.

Table 8
Estimation of the PLS-SEM structural model by size.

Relationship	Micro (A)	Small (B)	Medium (C)	Difference A)-B)	Difference A)-C)	DifferenceB)-C)
	β	β	B			
Effect on Integration						
Sensor	0.752***	0.730***	0.777***	0.022	−0.025	−0.047
Effect on Intelligent						
Sensor	0.393***	0.356***	0.398***	0.037	−0.005	−0.042
Integration	0.510***	0.496***	0.509***	0.014	0.001	−0.013
Effect on Response						
Sensor	0.303*	0.313***	0.177	−0.010	0.126	0.136
Integration	0.541***	0.486***	0.583***	0.056	−0.041	−0.097
Intelligent	0.150	0.200***	0.215	−0.050	−0.065	−0.015

Significance level. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

estimates of PLS-SEM.

5. Discussion and conclusion

5.1. Summary of findings

The overview of our results is reported in Table 9. The results of PLS-SEM analysis show that higher adoption of technologies associated with the Sensor layer increases the implementation of technologies associated with the Integration, the Intelligent, and the Response layer, leading to full support *H1a, H1b* and *H1c*. Moreover, the results of NCA analysis indicate that the technologies associated with the Sensor layer are a necessary condition for the adoption of the Integration, the Intelligent, and the Response layer technologies, thus confirming *H4a, H4b* and *H4c*.

Likewise, we found that higher adoption of the Integration layer technologies increases both the Intelligent and the Response layer, hence supporting *H2a* and *H2b*. Furthermore, the Integration layer is also a bottleneck for both the Intelligent and Response layers. Consequently, both *H5a* and *H5b* are confirmed.

Finally, higher adoption of the Intelligent layer increases the Response layer technologies, in line with *H3*. Furthermore, the Intelligent layer is a necessary condition for the Response layer, hence confirming *H6*.

In sum, these results highlight the role of enablers and enhancers played by the technologies associated with the lower layers, whose implementation is a necessary condition for the adoption of the technologies associated with the upper layers and the lower layers also contribute considerably to the variance in the upper layer. As shown by our robustness checks, these results appear to be stable both in SMEs operating in different sectors and characterized by different sizes.

5.2. Theoretical contributions

Our results provide several theoretical contributions to the analysis of the implementation pattern of digital transformation by SMEs, to the role played by Industry 4.0 technologies in the improvement of the firm's information processing capabilities, and to the combination of PLS-SEM and NCA methods for the analysis of managerial issues.

First, our paper clarifies the paths followed by SMEs in the adoption of digital technologies. In this sense, our analysis contributes to solving an existing gap in the literature that is related to the implementation paths of digital transformation by SMEs (Frank et al., 2019; Masood and Sonntag, 2020). Indeed, the literature has proposed several maturity models to support digital transformation, but these are not focused on SMEs (Mittal et al., 2018; Rafael et al., 2020). In particular, these maturity models may be not able to correctly account for their limited financial, human, and managerial resources, which may constraint SME capability to implement the different Industry 4.0 technologies (Nguyen et al., 2015). Besides, existing maturity models do not adequately investigate the relationships between the different technologies necessary for digital transformation. In fact, the transition toward digital transformation by SMEs may be hindered by the need to effectively bring together and combine Industry 4.0 technologies that are characterized by different and complementary functions (Horváth and Szabó, 2019; Mittal et al., 2018). By clarifying the actual relationships between the different technologies that contribute to digital transformation, the present paper provides a more realistic view of its implementation path, thus overcoming the limitations of traditional maturity models (Frank et al., 2019). Specifically, the application of PLS-SEM and NCA allows us to clarify how SMEs implement digital transformation by using a systematic approach that is aligned with the framework proposed by Lu and Weng (2018) and based on previous analysis on Internet of Things (Aydos et al., 2019; Haghparast et al., 2021). In particular, our analysis shows that digital technologies associated with Industry 4.0 can be

Table 9
Overview of findings.

Relationship	Contribute to the variance in the outcome		Necessary condition		Interpretation
	PLS-SEM result (Table 5)	Hypothesis	NCA result (Table 6)	Hypothesis	
Effect of Sensor on Integration	Significant determinant	H1a	Significant necessary condition	H4a	A certain level of Sensor layer is necessary for the adoption of Integration layer. An increase in the level of Sensor layer will increase Integration layer.
Effect of Sensor on Intelligent	Significant determinant	H1b	Significant necessary condition	H4b	A certain level of Sensor layer is necessary for the adoption of Intelligent layer. An increase in the level of Sensor layer will increase Intelligent layer.
Effect of Sensor on Response	Significant determinant	H1c	Significant necessary condition	H4c	A certain level of Sensor layer is necessary for the adoption of Response layer. An increase in the level of Sensor layer will increase Response layer.
Effect of Integration on Intelligent	Significant determinant	H2a	Significant necessary condition	H5a	A certain level of Integration layer is necessary for the adoption of Intelligent layer. An increase in the level of Integration layer will increase Intelligent layer.
Effect of Integration on Response	Significant determinant	H2b	Significant necessary condition	H5b	A certain level of Integration layer is necessary for the adoption of Response layer. An increase in the level of Integration layer will increase Response layer.
Effect of Intelligent on Response	Significant determinant	H3	Significant necessary condition	H6	A certain level of Intelligent layer is necessary for the adoption of Response layer. An increase in the level of Intelligent layer will increase Response layer.

classified into four hierarchical layers, i.e. Sensor, Integration, Intelligence, and Response, that are in charge, respectively, of the collection, combination, processing and use of organizational data. Our results confirm that the implementation of these layers is not based on a standalone approach since the lower layers enable and enhance the adoption of the upper layers. These results, as shown by our post-hoc analyses, appear to be stable both in SMEs operating in different sectors and characterized by different sizes. Hence, SMEs characterized by different sectors and/or sizes have the same implementation path, in terms of relationships among the adoption degrees of the different technological layers, even if they may have a peculiar propensity towards digital transformation (Brock and Von Wangenheim, 2019; Mittal et al., 2018).

Since our framework classifies Industry 4.0 technologies in accordance with the involvement in the management of organizational data, it may shed further light on the impact of the resulting infrastructure on the development of the firm's information processing capability. Indeed, previous studies based on Resource Based View and Information Processing View (Birkel and Hartmann, 2020; Li et al., 2020; Somohano-Rodríguez et al., 2020) have already discussed how some Industry 4.0 technologies represent a critical resource for the development of the firm's information processing capability. Nevertheless, these papers are focused on the analysis of either a single technology or the plain coexistence of more technologies in the same firm, without considering how they are implemented and combined with each other. The proposed framework allows us to understand how SMEs can improve their information processing capability by adequately combining digital technologies, which are characterized by a peculiar function in the management of organizational data. Specifically, the technologies associated with the Sensor layer have major enabling and enhancing roles for all the upper layers, especially considering the total effects. PLS-SEM shows that Sensor technologies have a larger direct effect on the Integration layer, indicating that the adoption of more advanced technologies for data collection enhances the SMEs' propensity to invest in Integration technologies (Matt and Rauch, 2020; Rauch et al., 2019). The comparison between the direct effects on the Intelligent and Response layers, estimated by the PLS-SEM model, suggests that their implementation is stimulated more by a higher level of Integration than Sensor technologies. On the other hand, our NCA results show that the technologies associated with the Integration layer are medium enablers of Intelligent and Response technologies. These partially contradictory results may be explained by SMEs that heavily adopt Integration technologies tend to exploit the resulting combined data by implementing more advanced Intelligent and Response technologies (Dremel et al., 2017; Kritzinger et al., 2018). In any case, the results on Sensor and Integration layers highlight the relevance of base technologies for the digital transformation of SMEs, as previously suggested by Frank et al. (2019) and Gillani et al. (2020). Conversely, the implementation of Intelligent technologies by SMEs seems to be still limited, in line with previous studies (Dalenogare et al., 2018), thus preventing the adoption of more advanced Response technologies. In any case, the implementation of the existing Response technologies seems to be enabled by Intelligent technologies, which allow the computation of the necessary data analytics (Chen et al., 2015; My, 2021). In sum, the results of our framework suggest that the infrastructure defined by SMEs for digital transformation is mainly based on the enabling role of Sensor technologies and the enhancing role of both Sensor and Integration technologies, while the role of Intelligence technologies appears still limited. In line with the Information Processing View, such an implementation path may affect the SMEs' information processing capability, which may be constrained by the limited use of organizational data processed by Intelligent technologies, like big data and analytics. In any case, to validate this insight, future studies should combine the analysis of technological resources with some human and managerial resources that may significantly affect the development of the firm's information processing capability.

These future studies may avail of the joint application of PLS-SEM and NCA, which allows us to differentiate the enabler (must-have factors) and enhancer (should-have factors) role played by different technologies in SMEs' digital transformation. The combined application of these methods in the management literature is still limited (Richter et al., 2021) and the joint adoption of NCA and PLS-SEM can favour a better understanding of the internal and external conditions that enable the occurrence of organizational phenomena, guaranteeing a clearer disentanglement of the role played by each determinant.

5.3. *Practical contributions*

Other than these theoretical contributions, the present work can also offer some practical contributions for SME managers and policymakers. Specifically, the operationalization of the proposed framework and the questionnaire in Appendix A may support managers interested in the implementation of digital transformation, thus overcoming the existing lack of adoption roadmaps specifically targeted to SME requirements. In this sense, our results show that, when implementing these technologies, managers should consider their heterogeneity and relationships, by balancing the investments on the technologies associated with different layers and by improving the relationships among these layers. In particular, the implementation of the upper layers, i.e. the Integration, Intelligent and Response ones, needs certain levels of adoption of the lowest layer, i.e. the Sensor one, as highlighted by our NCA results. By taking carefully into consideration these relationships, managers can fully exploit the potential benefits of digital transformation, overcoming the limits of an approach based on the stand-alone adoption of each technology and guaranteeing an effective improvement of their information processing capability. Using our approach, it is possible to measure the implementation level of each technological layer. For example, before adopting an ERP, which belongs to the Response layer (see Table 1), a manager should check if the levels of Sensor, Integration, and Intelligent layers are above the minimum threshold suggested by NCA (see Table 6).

The present paper may also support policymakers interested in the improvement of digital transformation by SMEs. In this sense, the framework analysed in this paper may lead to the development of more effective policies that take into account the actual implementation paths adopted by SMEs, rather than the overall investments on Industry 4.0 technologies or some normative roadmaps based on ideal models of digital transformation. For example, policies aiming at promoting the adoption of Intelligent and Response technologies risk being scarcely effective if SMEs have not yet reached a certain adoption degree of Sensor technologies, as shown in Table 6. For this reason, our work allows us to inform strategies and policies at the national and regional level, providing to policymakers the guidelines to better formulate financial supporting programmes and assessment schemes for evaluating digital projects presented by firms. For example, if regional firms show a very low level of technologies for digital data collection (i.e. Sensor layer), it is not appropriate to design policies aiming at increasing the use of artificial intelligence (i.e. Intelligent layer) by these firms. Similarly, the evaluation of incentive applications submitted by firms, for example for the adoption of a new autonomous robot or an automated warehouse, should check if these firms have the minimum level of sensors indicated in Table 6.

To summarize, our analysis suggests that, since the existence of specific technological adoption paths, innovation policies should be based on a systemic approach that considers the peculiarities and relationships of each technology.

5.4. *Limitations and future developments*

To provide more advanced theoretical and practical contributions, we aim at developing further studies in the next future, so as to overcome the limitations of the current paper. Specifically, this work is affected by some methodological limitations that may reduce the validity and generalization of its results.

First, for the reason described in Section 3.1, our sample is made up of SMEs with a positive economic performance in the last three years. This choice may reduce the generalization of our results and prevent a complete analysis of the effect of the economic conditions on digital transformation.

Second, the present paper does not evaluate the effects of several organizational variables, differently from SME industry and size, which may affect the capability to effectively implement digital transformation. In the future, we aim at overcoming this limitation by investigating the role of other organizational variables, like those associated with some human and managerial resources, which may affect the development of SMEs' information processing capability. A full understanding of this phenomenon requires the joint analysis of technological, human, and managerial resources, which may provide a more systematic analysis of SME digital transformation.

Moreover, by combining such an analysis with firm economic and financial performances, we will also evaluate the long-run effect of digital transformation on SME competitive advantage, thus measuring the value added by their infrastructure resulting from the combination of Industry 4.0 technologies.

Data availability

The authors do not have permission to share data.

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Appendix A. 1

Survey items

Layer	ID	Item
Sensor	01	Data on financial performance are digitally recorded in real-time
	02	Data on process performance are digitally recorded in real-time
	03	Tags for materials are assigned at their entrance in the firm
	04	The firm tracks the position of each product within the bins
	05	Each task carried out by robots on products is digitally recorded in real-time
	06	Handling machines track the position of each product inside them
	07	Vehicles are tracked by reliable tools located in their whole routes
	08	The firm has a digital archive of post-sales data
	09	Customer feedbacks are digitally recorded by the firm
	10	The firm has a digital archive of R&D data
	11	The firm has a digital archive of maintenance data
	12	Quality control involves the whole production system
Integration	01	The firm uses digital Kanban tags within its production system
	02	Tracking of tags for products is integrated into the whole supply chain
	03	Data used by machine tools are constantly available and updated
	04	Data used by measuring instruments are constantly available and updated
	05	Data used by assembly systems are constantly available and updated
	06	Data used by other digital machinery are constantly available and updated
	07	Purchasing data are integrated into the whole supply chain
	08	Forecasting data are integrated into the whole supply chain
	09	Post-sales data are integrated into the whole supply chain
Intelligent	01	In the Kanban system, Work in Process is digitally computed in real-time by reliable tools
	02	Purchasing data are validated and analysed together with other data
	03	Sales data are analysed in real-time by reliable tools
	04	Post-sales data are validated and analysed together with other data
	05	Marketing data are validated and analysed together with other data
	06	R&D data are constantly analysed by reliable tools
	07	Maintenance data are validated and analysed together with other data
Response	01	The firm uses quantitative, rather than qualitative forecasting techniques
	02	The firm uses Collaborative Planning, Forecasting and Replenishment fully integrated with the other actors of its supply chain
	03	The firm uses SCEM techniques to constantly monitor and immediately manage issues in the whole supply chain
	04	The firm adopts Visual planning by using digital interactive screens
	05	Assembly systems automatically interact with other machinery
	06	Handling machines in the inventory are based on flexible, rather than fixed paths
	07	Handling machines in the production system are based on flexible, rather than fixed paths
	08	Transportation management is intensively supported by Transportation Management System applications
	09	Inventory management is carried out by reliable tools
	10	Quality non-compliances automatically generate alarm messages
	11	Different machines share data on the production scheduling
	12	Production short-term rescheduling is managed by using reliable tools

Appendix B. 2

Table B.1
Correlation table among the constructs

	Sensor	Integration	Intelligent	Response
Sensor	1.000			
Integration	0.755	1.000		
Intelligent	0.743	0.779	1.000	
Response	0.817	0.882	0.809	1.000

Table B.2

Original estimates			Gaussian Copula estimates							
Relationship	β	p	β	p	B	p	β	p	β	p
Effect on Integration			Model 1							
Sensor	0.755	<0.001	1.636	<0.001						
Sensor_copula			−0.866	0.005						
Effect on Intelligent			Model 2		Model 3		Model 4			
Sensor	0.359	<0.001	0.290	0.109	0.359	0.065	0.365	<0.001		
Integration	0.508	<0.001	0.707	<0.001	0.508	<0.001	0.693	<0.001		
Sensor_copula			0.069	0.641	0.001	0.999				
Integration_copula			−0.228	0.008			−0.220	0.008		
Effect on Response			Model 5		Model 6		Model 7		Model 8	
Sensor	0.278	<0.001	0.465	0.004	0.516	0.003	0.295	<0.001	0.466	0.003
Integration	0.516	<0.001	0.674	<0.001	0.483	<0.001	0.703	<0.001	0.687	<0.001
Intelligence	0.201	<0.001	0.226	0.006	0.293	0.001	0.231	0.005	0.184	<0.001
Sensor_copula			−0.157	0.261	−0.211	0.174			−0.161	0.240
Integration_copula			−0.203	<0.001			−0.219	<0.001	−0.212	<0.001
Intelligence_copula			−0.041	0.496	−0.093	0.148	−0.048	0.419		
Effect on Response			Model 9		Model 10		Model 11			
Sensor	0.278	<0.001	0.288	<0.001	0.291	<0.001	0.525	0.004		
Integration	0.516	<0.001	0.502	<0.001	0.719	<0.001	0.493	<0.001		
Intelligence	0.201	<0.001	0.308	<0.001	0.183	<0.001	0.201	<0.001		
Sensor_copula							−0.226	0.157		
Integration_copula					−0.230	<0.001				
Intelligence_copula			−0.108	0.080						

Appendix C. 3

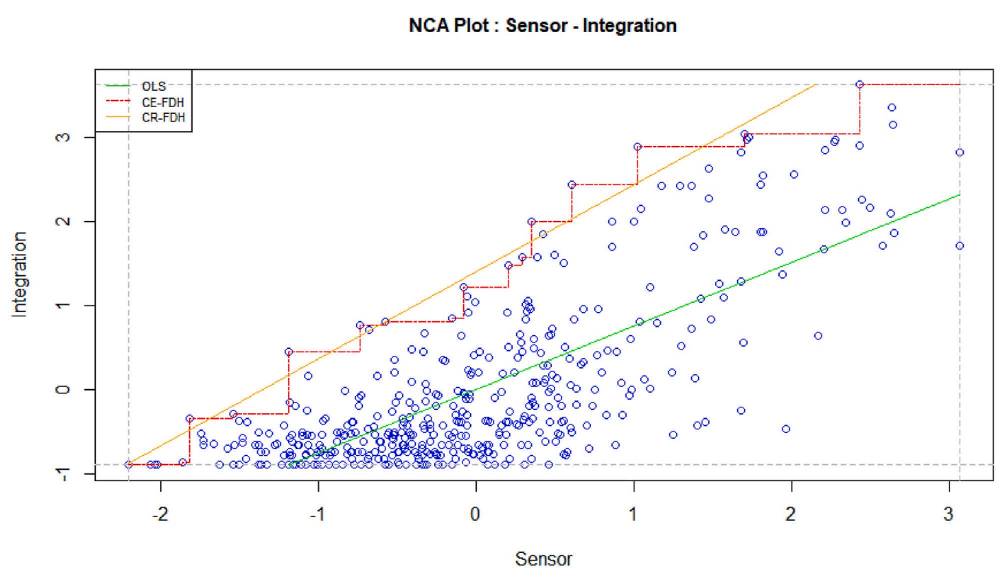

Fig. C.1. Scatter plot of the NCA between Sensor and Integration layers

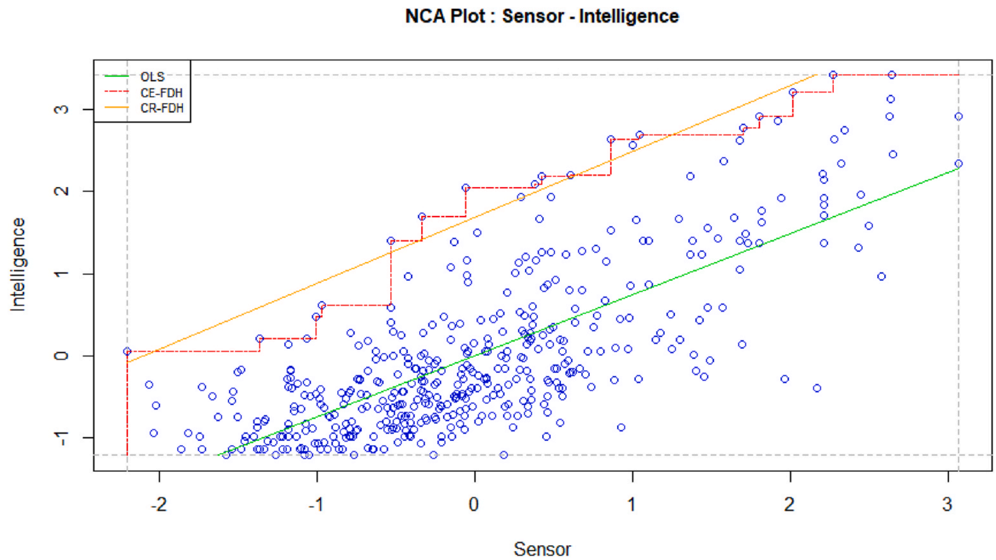

Fig. C.2. Scatter plot of the NCA between Sensor and Intelligent layers

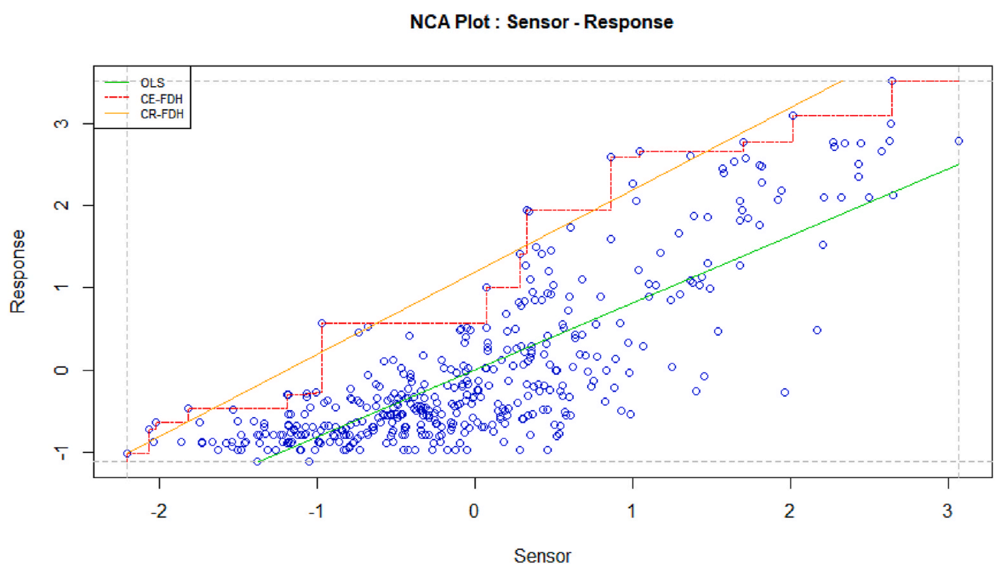

Fig. C.3. Scatter plot of the NCA between Sensor and Response layers

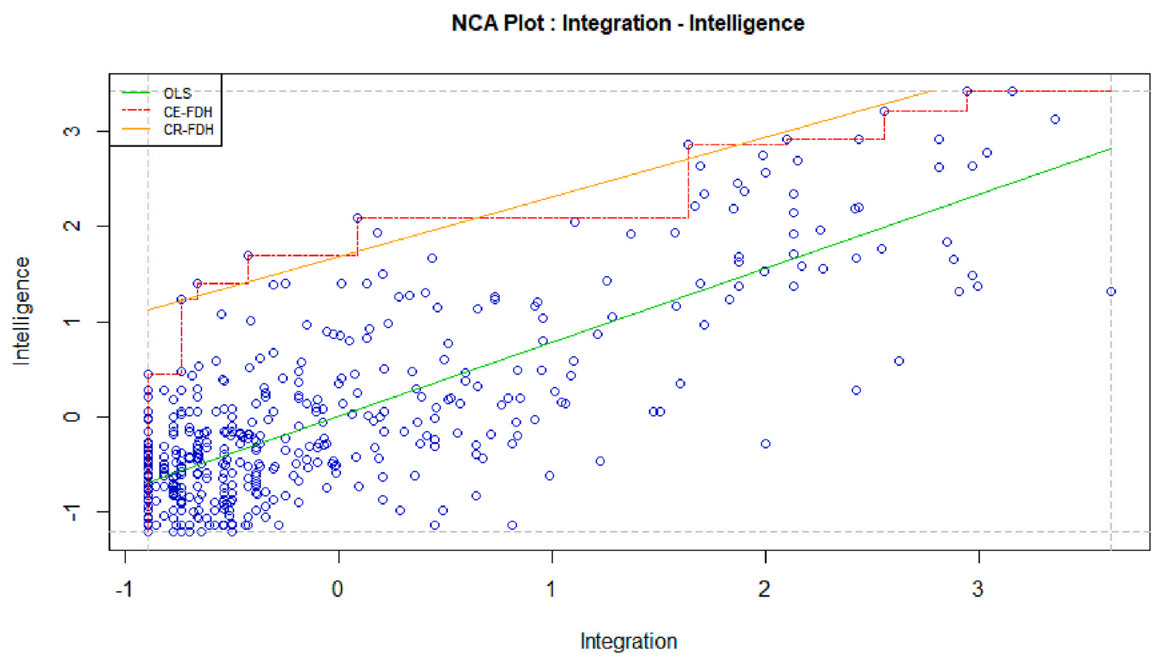

Fig. C.4. Scatter plot of the NCA between Integration and Intelligent layers

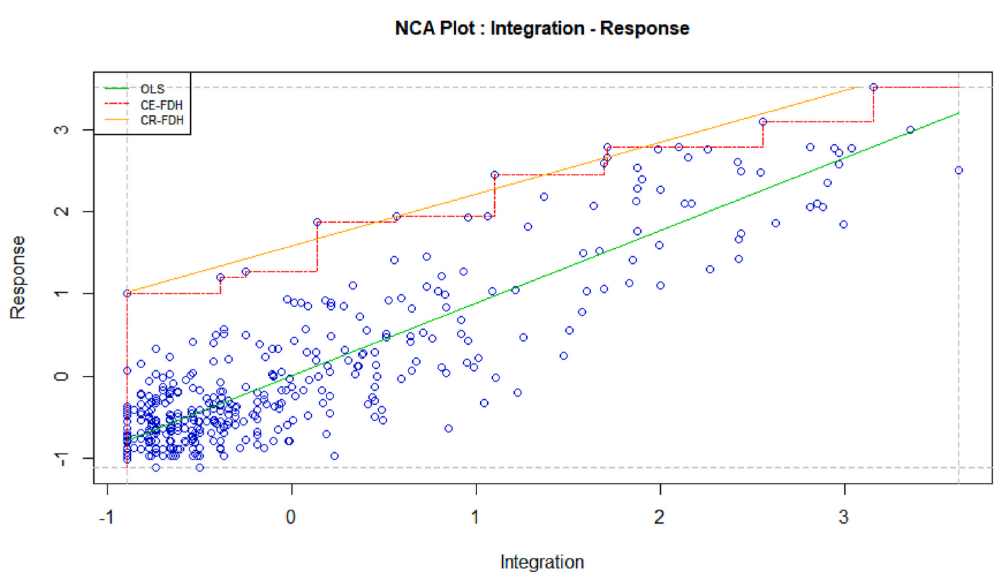

Fig. C.5. Scatter plot of the NCA between Integration and Response layers

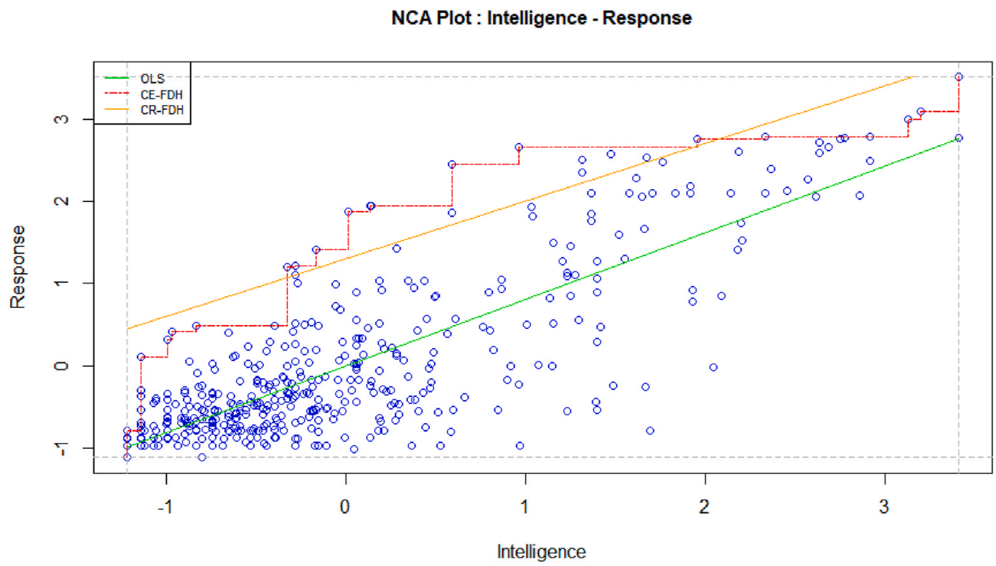

Fig. C.6. Scatter plot of the NCA between Intelligent and Response layers

Table C.1
Bottleneck table of the NCA between Sensor and Integration layers

Integration (percentage range)	Sensor (percentage range) – CE-FDH with cut-off = 0	Sensor (percentage range) - CR-FDH with cut-off = 0
0	NN	NN
10	7.3	7.9
20	19.2	16.2
30	27.8	24.5
40	40.2	32.8
50	45.7	41.1
60	48.4	49.4
70	53.4	57.7
80	61.3	66
90	87.9	74.3
100	87.9	82.6

NN: Not Necessary, NA: Not Available.

Table C.2
Bottleneck table of the NCA between Sensor and Intelligent layers

Intelligent (percentage range)	Sensor (percentage range) - CE-FDH with cut-off = 0	Sensor (percentage range) - CR-FDH with cut-off = 0
0	NN	NN
10	NN	NN
20	NN	NN
30	16	6.3
40	31.7	17.2
50	31.7	28.1
60	35.4	39.1
70	40.6	50
80	58.2	60.9
90	80	71.8
100	84.9	82.8

NN: Not Necessary, NA: Not Available.

Table C.3
Bottleneck table of the NCA between Sensor and Response layers

Response (percentage range)	Sensor (percentage range) - CE-FDH with cut-off = 0	Sensor (percentage range) - CR-FDH with cut-off = 0
0	NN	NN
10	3.4	6.9
20	23.4	15.7
30	23.4	24.5
40	43.2	33.2
50	47.2	42

(*continued on next page*)

Table C.3 (*continued*)

Response (percentage range)	Sensor (percentage range) - CE-FDH with cut-off = 0	Sensor (percentage range) - CR-FDH with cut-off = 0
60	48	50.8
70	58.2	59.6
80	58.2	68.3
90	80	77.1
100	91.9	85.9

NN: Not Necessary, NA: Not Available.

Table C.4
Bottleneck table of the NCA between Integration and Intelligent layers

Intelligent (percentage range)	Integration (percentage range) - CE-FDH with cut-off = 0	Integration (percentage range) - CR-FDH with cut-off = 0
0	NN	NN
10	NN	NN
20	NN	NN
30	NN	NN
40	3.4	NN
50	3.4	NN
60	10.4	15.6
70	21.7	32
80	56.1	48.4
90	76.4	64.8
100	85.1	81.2

NN: Not Necessary, NA: Not Available.

Table C.5
Bottleneck table of the NCA between Integration and Response layers

Response (percentage range)	Integration (percentage range) - CE-FDH with cut-off = 0	Integration (percentage range) - CR-FDH with cut-off = 0
0	NN	NN
10	NN	NN
20	NN	NN
30	NN	NN
40	NN	NN
50	11.3	6.3
60	22.8	22.5
70	44.2	38.8
80	57.3	55
90	76.4	71.3
100	89.7	87.6

NN: Not Necessary, NA: Not Available.

Table C.6
Bottleneck table of the NCA between Intelligent and Response layers

Response (percentage range)	Intelligent (percentage range) - CE-FDH with cut-off = 0	Intelligent (percentage range) - CR-FDH with cut-off = 0
0	NN	NN
10	1.7	NN
20	1.7	NN
30	4.8	NN
40	19.2	8.7
50	19.2	23
60	26.6	37.3
70	39	51.6
80	47	65.9
90	95.4	80.1
100	NA	94.4

NN: Not Necessary, NA: Not Available.

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