Value co-creation via machine learning from a configuration theory perspective

Claudia Presti, Federica De Santis and Francesca Bernini
Department of Economics and Management, University of Pisa, Pisa, Italy

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Abstract

Purpose – This paper aims to propose an interpretive framework to understand how machine learning (ML) affects the way companies interact with their ecosystem and how the introduction of digital technologies affects the value co-creation (VCC) process.

Design/methodology/approach – This study bases on configuration theory, which entails two main methodological phases. In the first phase the authors define the theoretically-derived interpretive framework through a literature review. In the second phase the authors adopt a case study methodology to inductively analyze the theoretically-derived domains and their relationships within a configuration.

Findings – ML enables multi-directional knowledge flows among value co-creators and expands the scope of VCC beyond the boundaries of the firm-client relationship. However, it determines a substantive imbalance in knowledge management power among the actors involved in VCC. ML positively impacts value co-creators' performance but also requires significant organizational changes. To benefit from VCC via ML, value co-creators must be aligned in terms of digital maturity.

Originality/value – The paper answers the call for more theoretical and empirical research on the impact of the introduction of Industry 4.0 technology in companies and their ecosystem. It intends to improve the understanding of how ML technology affects the determinants and the process of VCC by providing both a static and dynamic analysis of the topic.

Keywords Digitalization, Machine learning, Industry 4.0, Servitization, Configuration theory

Paper type Research paper

1. Introduction

Servitization and Industry 4.0 can be referred to as the main transformations that have dramatically changed the way companies are doing business, stimulating business model innovations in terms of product development and delivery, as well as in terms of the relationship between firms and their customers (Frank *et al.*, 2019a, b). Servitization refers to the shift from a product-centric business model to a pure service-oriented or a product-service-oriented one, according to a purported service-dominant logic, where companies combine tangible and intangible resources to develop product-service systems (PSS) trying to fulfill emerging customers' needs (Vargo and Lusch, 2004; Boehm and Thomas, 2013). A considerable amount of extant literature examines how servitization manifests itself and changes firms' value creation processes into value co-creation (VCC) ones (Grönroos, 2011; Lusch and Vargo, 2014). In parallel, researchers are showing a growing interest in investigating how Industry 4.0 and the related digital technologies are determining business model innovation in different industries (Jacobides *et al.*, 2018; Müller *et al.*, 2018).

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By analyzing the phenomenon of digital transformation in the context of servitization, it is possible to notice that the rapid development of digital technologies constitutes one of the most influential factors that facilitate the shift from a product orientation to a service orientation, since new technologies provide firms with significant opportunities to offer better products and services. Specifically, technology can foster product-service integration as it becomes the interface between products and services (Geum *et al.*, 2011; Boehm and Thomas, 2013).

Extant literature on servitization mainly adopts a managerial perspective and focuses on investigating the determinants of successful service implementation in terms of increasing the customer's perception of value. Simultaneously, Industry 4.0 research is still mostly technology-oriented, aimed at exploring how technological developments impact on firms' production processes and workforce, policy-making implications, and the return on investments in Industry 4.0 technologies. Conversely, this stream of literature rarely discusses the strategic view of the adoption of these technologies (Frank *et al.*, 2019a; Nazarov and Klarin, 2020; Wagire *et al.*, 2020; Naeem and Di Maria, 2021). However, few attempts are made to investigate how digital technologies impact servitization processes (Bolton *et al.*, 2018), and turn them into a digital servitization journey (Kohtamäki *et al.*, 2020; Troilo *et al.*, 2017; Uden and del Vecchio, 2018; Yoo *et al.*, 2010).

Several scholars underline that there is a paucity of research that investigates the different options and elements that can be considered when firms start a digital transformation endeavor (Hess *et al.*, 2016; Kohli and Melville, 2019). In fact, the relationship between digitalization and servitization must be regarded as a complex phenomenon, to be studied according to a holistic perspective. Contrastively, recent work in academia has mainly provided guides on specific aspects of digital transformation, while it failed to consider how product-service integration via digitalization can assume differentiated shapes according to the specific managerial and environmental circumstances (Geum *et al.*, 2011; Hess *et al.*, 2016; Kohli and Melville, 2019).

To fill this gap, this study aims at understanding how the introduction of digital technologies affects the value creation process through servitization. In order to investigate the interplay between digitalization and servitization in a real-life setting, one must consider the specific digital technology that is implemented. Among the Industry 4.0 technologies, machine learning (ML) can play a key role in stimulating business model innovation toward a servitization perspective. By equipping products with ML technologies, indeed, companies are able to collect and process huge volumes of data to predict future events and to suggest courses of action in uncertain conditions. ML has also the capability to accomplish tasks that are similar to that of human wisdom and decision-making (Mishra and Tripathi, 2021). ML can significantly contribute to customer engagement (Burgess, 2018), and this facilitates the provision of new products and services, thus fostering the continuous transformation of business activities (Porter and Heppelmann, 2014).

Therefore, this paper addresses the following research questions: How does ML contribute to servitization processes? What are the domains to be considered and how do they interact when ML is used to shift from a product-oriented business model to a product-service-oriented one?

To answer these questions, we based on configuration theory to propose an interpretive framework that explains the configuration of a VCC process via ML. A configuration inquiry entails structuring the investigation on two different levels: a static and a dynamic one (Dess *et al.*, 1993). Consistently, different methodologies are required. Through a literature review methodology, we conduct the static analysis, so that we defined the theoretically derived domains to be considered when analyzing the configuration of a VCC process via ML and the corresponding value drivers. Further, to conduct the dynamic analysis, we adopted a case study methodology aimed at investigating the association and the relationships between the various domains derived from the literature.

The present study offers useful contributions to several streams of literature. First, it contributes to the literature on Industry 4.0 and business model innovation, by answering the call for more research that explains how Industry 4.0 innovation is realized, in terms of enabling technologies and the corresponding effect on companies' business models (Nazarov and Klarin, 2020; Srivastava *et al.*, 2022; Marrucci *et al.*, 2023; Grooss *et al.*, 2022). Second, the study adds to the growing body of literature on VCC and digital servitization of manufacturing industries, by providing an interpretive framework that highlights what are the most relevant domains and thus the determinants of this phenomenon, and the interrelationships among these domains. Particularly, our study answers the call for more research on Industry 4.0 and VCC in industrial services (Wagire *et al.*, 2020). Finally, we more broadly contribute to the realization of configuration theory's potential (Short *et al.*, 2008) by applying it to a different setting such as business model innovation via digital servitization.

The remainder of this paper is structured as follows. The next section outlines the theoretical background. The third section introduces the methodology adopted in this study. The fourth section presents the theoretical framework emerging from the traditional literature review. The section thereafter presents the empirical research finding, where we propose the interpretive framework. In the final section we discuss the results and highlight the main contributions of the study, also providing the limitations of the paper and suggestions regarding future research.

2. Theoretical background

2.1 Servitization in the industry 4.0 context

Servitization pushes firms to answer the increasing commoditization of products, by innovating their business models and shifting their focus "from selling products to offering a combination of products and services" (Naik *et al.*, 2020). By adopting this approach, manufacturing companies offer "a bundle of integrated products and services" (Frank *et al.*, 2019b) i.e. a PSS, where goods are considered as a means for the provision of services that provide functionalities to customers and other stakeholders. In such a scenario, the value creation potential of firms' offering benefits from the interactions between the firms and their clients. Servitization thus exerts a significant impact on the redefinition of the relationship between companies and customers since companies get the opportunity to create value together with their customers (Grönroos, 2011). This leads to a new conception of value, that becomes co-created among the firm and its clients (Vargo and Lusch, 2004; Uden and del Vecchio, 2018).

Extant literature points out that the process of value creation can be interpreted in two main and contradictory approaches. According to the first approach, value creation is an all-encompassing process that includes as value creating activities those performed by both the provider (manufacturer) and the user (customer), i.e. where the value creation process starts from the product design and ends with the customer's use of the provided product (Vargo and Lusch, 2008). The other approach, instead, starts from the assumption that design, development and manufacturing of resources and back-office processes (purported production activities), are not part of value creation, which is thus defined as the customer's creation of value-in-use (Grönroos, 2008). Only when the customer is involved in production activities, they may become part of value creation (Grönroos, 2011). Table 1 summarizes the main contributions that provide interpretive frameworks on servitization and VCC.

In such a scenario, digital technologies can represent one of the most influential circumstances that enables customers' involvement in production activities, thus reshaping the concept of value creation. Over the last decade, the purported digital revolution led to the emergence of the concepts of Industry 4.0 and smart factory, which are based on a strongly

Authors	Year	Title	Journal	VCC framework
Vargo and Lusch	2004	Evolving to a new dominant logic for marketing	*Journal of Marketing*	Service-centered dominant logic
Vargo *et al*	2008	On value and VCC: a service system and service logic perspective	*European Management Journal*	Service-dominant logic on value creation
Grönroos	2011	Value co-creation in service logic: A critical analysis	*Marketing Theory*	Toward a service logic: value creation and co-creation revisited
Vargo and Lusch	2016	Institutions and axioms: an extension and update of service-dominant logic	*Journal of the Academy of Marketing Science*	The axioms of service-dominant logic
Uden and Del Vecchio	2018	Transforming the stakeholders' Big Data for intellectual capital management	*Meditari Accountancy Research*	TADERT model of co-creation
Xie *et al*	2016	VCC between firms and customers: the role of big data-based cooperative assets	*Information and Management*	Theoretical framework of cooperative assets

Source(s): Author's own creation

Table 1.
Literature on VCC

transformed use of technologies within companies (Schwab, 2017; Gourisaria *et al.*, 2021). Particularly, the shift from traditional manufacturing to the concept of smart factory mainly derives from the huge amounts of data made available by the digital transformation of the world, where "almost anything can be recorded, measured, and captured digitally, and thereby turned into data" (Cao *et al.*, 2015, p. 423). In fact, Industry 4.0 encompasses a set of "enabling technologies" (Ustundag and Cevikcan, 2018) able to turn such data deluge into meaningful knowledge (Presti, 2022). Although a complete list of these enabling technologies does not exist in literature yet, one can refer to Cyber-Physical Systems, Internet of Things, Big Data, Data Analytics, Cloud Computing, Blockchain, Machine Learning and Artificial Intelligence (Naeem and Di Maria, 2021).

Innovation according to an Industry 4.0 perspective means that companies can exploit these enabling technologies to generate new products, services and processes or to drive business model innovation, to establishing a competitive advantage (Capurro *et al.*, 2021; Kohtamäki *et al.*, 2020; De Santis and Presti, 2018; Visvizi *et al.*, 2021). Within their path toward Industry 4.0 innovation, companies can find themselves on different status of digital maturity, depending on what they have already achieved in terms of digital transformation efforts (Ochoa-Urrego and Peña-Reyes, 2021; Chanias and Hess, 2016).

Industry 4.0 technologies are "interactive by nature" (Naeem and Di Maria, 2021, p. 638) and have the potential to revolutionize the way in which firms create and capture business value (Yoo *et al.*, 2010). Among Industry 4.0 technologies, machine learning (ML) can play a pivotal role in revolutionizing business, due to its ability to automatically identify patterns by analyzing huge volumes of data and using these patterns to predict future events (predictive capability) or to make decisions in uncertain conditions (prescriptive capability). ML has also a learning capability, which means that the results from previous previsions and prescriptions are used in a way that emulates human reasoning to progressively improve the ML's predictive and prescriptive capabilities (Murphy, 2012). Within the smart factories, these ML's capabilities can revolutionize the decision-making, the production processes and the relationship between the company and its customers (Oluyisola *et al.*, 2022). In particular, ML increases production processes' flexibility and efficiency, by making them interconnected, smart and customized (Lee and Lim, 2021). For instance, ML enables predictive maintenance based on the analysis of large amounts of realistic data on plants' functioning, thus contributing to minimizing downtimes or maximizing the plants' performance (Gourisaria *et al.*, 2021).

The interplay between servitization and digital transformation gives rise to the concept of digital servitization, which can be defined as "the use of digital technologies to create and appropriate value from product-service offerings" (Kohtamäki *et al.*, 2020, p. 4). In other words, digital servitization refers to the use of digital technologies for facilitating the development of new types of service innovation (Coreynen *et al.*, 2017). In particular, digital servitization uses Industry 4.0 enabling technologies to offer new functionalities of the connected products and to integrate various operational processes to increase opportunities for value creation through advanced service offerings (Porter and Heppelmann, 2014). In fact, Industry 4.0 technologies bring such an interactive capability that they can become the interface between products and services, thus stimulating product-service integration (Geum *et al.*, 2011; Boehm and Thomas, 2013). This implies an increasing involvement of clients in companies' value proposition and fosters the creation of new digitally enabled PSS (Kohtamäki *et al.*, 2020; Opresnik and Taisch, 2015). As such, by combining the relational perspective brought by servitization with the interactive potential of digital technologies, a new vision of value creation emerges (Xie *et al.*, 2016), that is conceived as a "value-in-interactional creation" and is realized through an interactive and cyclical co-creation process between the company and its clients (Ramaswamy and Ozcan, 2018). Due to the vast abundance of enabling technologies mentioned above, and the different contextual factors that can impact the relationship between a firm and its environment (Gersick, 1991; Hannan and Freeman, 1989), to properly investigate how digitalization and servitization interact in a real-life setting, one needs to take into account the specific digital technology that is implemented. In this respect, we choose to focus on ML as this technology has proven to foster significant innovation opportunities in terms of transforming the manufacturing processes and the company–client relationship (Naik *et al.*, 2020), and contributes to shift value creation endeavors from a shareholders' perspective to the concept of VCC.

Scholars are increasingly showing interest in investigating the potential and the impact of digital transformation on companies' servitization strategies and on their relationship with customers. However, the literature devoted to the analysis of a possible path for creating value with ML and other Industry 4.0 technologies is based mainly on a marketing perspective, as it focuses on the factors determining successful implementation of digital servitization (Ramaswamy and Ozcan, 2018; Rangaswamy *et al.*, 2020; Puntoni *et al.*, 2021).

By reviewing ML and other Industry 4.0 research, it has emerged that there is a paucity of contributions analyzing how digital service ecosystems change companies' operational processes, rethink their business models and define new sources of value (Nazarov and Klarin, 2020). Most of the literature on this topic, in fact, is mainly focused on analyzing how technological developments impact firms' production processes and workforce, policy-making implications and the return on investments in Industry 4.0 technologies (Frank *et al.*, 2019a; Naeem and Di Maria, 2021). Therefore, there is a scant of research that investigates how digital technologies affect servitization processes (Bolton *et al.*, 2018; Wagire *et al.*, 2020), and transform them into digital servitization ones (Kohtamäki *et al.*, 2020; Troilo *et al.*, 2017; Uden and del Vecchio, 2018; Yoo *et al.*, 2010).

Specifically, scholars underline that there is a lack of contributions that examine the different options and elements to be considered when firms start a digital transformation endeavor (Hess *et al.*, 2016; Kohli and Melville, 2019). The relationship between digitalization and servitization must be regarded as a complex phenomenon, to be studied according to a holistic perspective, able to show that the exploitation of the opportunities provided by digital technologies in VCC processes might require different configurations (Reck and Fliaster, 2018). In this respect, numerous scholars point out that recent work in academia has been largely concerned with providing guidance on certain aspects of digital transformation, while it failed to consider how product-service integration via digitalization can assume differentiated shapes according to the specific managerial needs and environmental conditions (Geum *et al.*, 2011; Hess *et al.*, 2016; Kohli and Melville, 2019).

To fill this gap, we based on configuration theory to understand how digital servitization can manifest itself according to many different paths, resulting from the interaction among multiple forces. The configuration approach allows developing a conceptual framework that does not focus solely upon specific contingent variables (Auzair, 2015) but tries to highlight the domains to be considered and their interrelationships that contribute to a digital servitization journey.

2.2 Configuration theory

A configuration represents a multidimensional entity made of peculiar and separate features that are tightly interrelated and mutually reinforcing, so that they are significant jointly rather than individually (Dess *et al.*, 1993). When investigating a complex phenomenon, it is not possible to assume that these features are linked by linear or cause-and-effect relationships (Perera, 2023), but a holistic posture is required, aimed at exploring how these multidimensional entities interact to create order within an organization (Meyer *et al.*, 1993; Miller, 1996). According to configuration theory, indeed, multiple conditions can lead to the same outcome (Fiss, 2007; Woodside, 2014). That is to say that different ways of achieving the outcome co-exist (Woodside, 2017). Therefore, when research is in its exploratory stage of development, such approach can be particularly useful since it allows to identify the flexible set of interacting elements (Meyer *et al.*, 1993) that define the company's posture when a new phenomenon occurs, as in the case of digital servitization. This is an essential research step if one wants to identify the different possible configurations, by means, for example, of cluster analyses that would provide a taxonomy (Miller, 1996; Short *et al.*, 2008).

Configuration inquiries consist of a static and a dynamic phase. When conducting the static analysis, one must first identify the conceptual building blocks of a configuration – i.e. a multi-shaped arrangement of its different domains (Dess *et al.*, 1993). The dynamic analysis in configuration studies provides an empirical basis to sharpen up and spread existing conceptual frameworks and theoretical assumptions (Bedford and Malmi, 2015; Corso *et al.*, 2003).

The central assumption when adopting this approach is that organizations tend to show similar arrangements when operating according to resembling exogenous and endogenous forces (Gersick, 1991). Exogenous forces refer to the environmental, competitive and institutional setting, while endogenous forces relate to the specific and internally consistent characteristics of an organization that act to limit the number of possible configurations (Child, 1972; Hannan and Freeman, 1989). The interaction among exogenous and endogenous forces implies that, among the finite number of possible configurations, organizations tend to adopt the one that best fits their specific characteristics (Bedford and Malmi, 2015).

Business model innovation determined using digital technology to carry out VCC processes is a complex phenomenon, which involves the interaction between endogenous and exogenous variables and does not take the form of a simple cause-effect relationship. Therefore, when investigating the opportunities that new technology provides in business contexts, it is necessary to consider the whole configuration, within which technology represents just one feature (Reck and Fliaster, 2018). In fact, the adoption of a new technology *per se* does not automatically imply a shift of the company's business model toward a VCC perspective. Similarly, the adoption of a VCC perspective can assume different characteristics depending on what are the specific interacting forces (e.g. those related to the introduction of digital technologies) that lead to such business model innovation.

To develop an interpretive framework that identifies the domains of the possible configurations of a VCC process when ML technology is adopted, we followed a research path that involves two different methodologies. First, we deductively identified domains by means of a traditional literature review to define a theoretical framework on VCC in ML-enabled contexts (see section 4). Second, we conducted a case study to complement the theoretical framework and we investigated the dynamic relationships among the configuration's domains. Accordingly, we propose an interpretive framework of VCC via ML (see section 5).

3. Methodology

In configuration inquiry, researchers must not limit themselves to the use of quantitative methodologies, as a configuration represents a holistic stance aimed at explaining how order emerges from the different elements as a whole (Meyer *et al.*, 1993). Since research in the field under investigation is still in its developmental stage, qualitative studies can enlighten new domains and relationships not already mapped by theoretical essays and explore them in a real-life setting (Dess *et al.*, 1993).

To reach the aim of this paper, we followed a research path that involves two different methodologies. For the static analysis, we deductively identified domains by means of a traditional literature review, aimed at extracting, summarizing and reinterpreting the cumulative set of previous contributions on the topic (Denyer and Tranfield, 2006). In this stage we defined the theoretically-derived framework of VCC in ML-enabled contexts (see section 4) that we will use to interpret the empirical findings.

Subsequently, through a case study methodology (Yin, 2017), it was possible to inductively analyze the theoretically-derived domains and their relationships within a configuration (Dess *et al.*, 1993), thus complementing the static analysis and carrying out the dynamic one (see section 5). Indeed, the case study methodology allows researchers to analyze in detail how various elements of the specific VCC configuration can be operationalized (Kreiser *et al.*, 2021).

Therefore, this study provides the first elements of a configuration (namely the domains) and also a dynamic view of their connections. Since this study refers to a topic that has not been studied before and our aim is to learn about new aspects of existing knowledge and start investigating this field to provide the first step for further studies, we can define this study as exploratory.

3.1 Case selection

For the case study, we involved the Italian company Dilorean (invented name), which is an international Group, a leader in the sector in which it operates, with strategic branches in the United States and Asia. The company operates in B2B and supplies complete production lines and machinery retrofits all over the world, committing to quality and customer service.

This case fits with our research purpose for the following reasons. First, Dilorean is committed to continuous customer assistance throughout the entire life cycle of its products. Second, it installs a system of sensors in all the sold types of machinery to collect all clients' production data. Finally, the company has developed internally a ML algorithm (Gold System), which analyzes all the data collected via sensors to extract knowledge on the use of its products by client companies to provide personalized services and gain insights for product development. Simultaneously, the knowledge extracted by sensor data provides its clients with the opportunity to improve the use of the sold product in terms of efficiency and effectiveness.

Stemming from the above, the Dilorean case study allows us to analyze the implications of using ML technologies for the development of full-fledged PSS, by looking at the two perspectives of VCC processes: that of the manufacturer (i.e. Dilorean) and that of its clients. The selected case can be traced back to the category of "critical cases" as we adopted an inductive-deductive approach (Otley and Berry, 1994; Thompson, 2022) to shed light on the dynamics between the domains of the VCC, within a business context characterized by the drive toward technological innovation.

3.2 Data collection

Our research is based on three main data collection methodologies: documentary analyses, observation and interviews (see Table 2).

Data available on online public documents allowed us to be sure that the case that we identified was consistent with the research purpose and to deepen our understanding of Dilorian's disclosed values, target market and competitors.

In October 2019, we conducted three interviews with the following Dilorean's actors: the President and managing director of the company (D01); the coordinator of the engineering and automation department and digital innovation (D02); one of the managers of the engineering and automation department (D03). Each interview lasted about an hour, and it was conducted at the company's headquarters.

Carrying out the interview in person at Dilorean's headquarters allowed us to complement the data collection with direct observation of the functioning of Gold System, specifically the way Dilorean continuously monitors its clients through the dashboard and the extraction of reports. Moreover, by visiting Dilorean, we observed the changes that the introduction of the Gold System has determined at the organizational structural level. Semi-structured interviews made it possible to analyze the investigated topic based on the perspectives, experiences, nuances and contradictions of the interviewees' opinions (Silverman, 2013). Interviews allowed researchers to understand the point of view of the interlocutors regarding the connections between particular events and phenomena, as well as to discuss any new issues that emerged during the interview (Gillham, 2005). To this end, we prepared a list of questions based on the theoretically derived domains presented in Section 4. As a way of example, we asked the interviewees "*Why did you decide to invest in ML technologies?*" to investigate what are the main driver of the firm's value proposition. Again, we asked *"For what purposes do you use the data collected through sensors and elaborated via ML?"* to understand whether data is considered as a resource to be integrated with VCC process.

However, when analyzing a configuration, it is possible that some relationships between variables are not acknowledged (Gerdin, 2005), thus we guaranteed the interviewees the opportunity to express themselves freely so that new issues could have emerged. To let

Data source	*Details*
Analysis of public online documents	• Social responsibility reports • Integrated annual reports
Private documents	• Reports of Gold System
Non-participant observation in Dilorean	• Client summary dashboard • Production units and administrative offices
Semi-structured interviews	• Language: Italian • Interviewees: o President and managing director of the company (D01); o Coordinator of the engineering and automation department and digital innovation (D02) o Manager of the engineering and automation department (D03) • Duration: 1 h each • Location: Company's headquarters

Source(s): Author's own creation

Table 2.
Data collection – documents, observations, interviews

respondents orienting the interview toward topics they considered more relevant, and that could have been neglected by the researchers, we asked a few broad questions such as: *"Did the introduction of ML require any change in your company?"* and *"Has ML changes in some ways the relationship with your clients?"*. All interviews were recorded and transcribed to allow researchers to rework and analyze the responses. Aiming at avoiding ex-post rationalizations by the interviewees, the information obtained by each of them was compared with the documents (Sandelin, 2008) and with the information provided by the other interviewees (Miller, 1996). Since the roles and the number of interviewees did not complete the landscape of the actors involved in the systems under examination, the analysis of reports extracted from the Gold System (i.e. the private documents) allowed us to better understand what types of data the system provided, their possible aggregations and potential uses of this information source (e.g. plan maintenance, suggest increases in production speed for individual customers, develop new products). Given the strategic nature of these reports, we were not allowed to take them outside the company, so we took notes of the structure and typology of data extracted, without reporting sensitive data, such as clients' name and their specific bugs in the production process.

3.3 Data analysis

The data analysis process consists of several phases presented below in sequential order (see Table 3). However, it was often necessary to go back to the previous phases or to review the literature to be sure of the clarity of the data interpretation process (Thompson, 2022).

Data analysis started with the individual researchers reading the gathered documentation and the interviews' transcripts. This phase was aimed at understanding the main topics covered during the interviews and their connections with the available documents. To keep track of the individual opinions on possible connections and aggregations emerged during this phase, we added comments to the transcripts, so that the process of unifying information sources started. It is worth underlining that in this phase the concepts were solely induced by the data.

The interviewees' responses and the other information sources were then summarized in Excel tables to reorganize the pieces of the interviews and other information sources by topic, thus making it possible to perform data triangulation. Based on the concepts outlined this way, each author has developed personal considerations. The comparison between the researchers' interpretations allowed highlighting some preliminary connections between the mapped concepts, which were then compared with the evidence deriving from observations,

Phases	*Involved researcher*	*Output*
Documents and interview transcript reading	Each researcher separately	Commented transcripts
First data reorganization	All the researchers together	Excel table organized by inductively-derived topic
Excel table analysis	Each researcher separately	Possible relationship between topics
Codes definition	All the researchers together	Inductive domain and sub-domain scheme
Second data reorganization	All the researchers together	Excel table organized by domain and sub-domains
Comparison with theoretical domains (Table 4)	All the researchers together	Final interpretive framework

Source(s): Author's own creation

Table 3.
Data analysis

interviews and documentary analyses to ensure that these were supported (Huberman and Miles, 2002). By creating a polyphony of voices and sources to be explored, it was possible to create an information platform deemed sufficiently credible and significant for the analysis of the phenomenon under investigation (Janesick, 1994).

Subsequently, the authors together created a summary scheme of the emerged issues, by codifying all the mapped concepts aiming at identifying the relevant domains. Further, we developed macro-, meso- and micro-level codes, to grasp the multifaceted relationships among these domains. As a way of example, at the macro-level, we distinguished two perspectives: that of Dilorean and that of client companies. Further, at a meso-level, we grouped under the code “ML impact_Dilorean” or “ML impact_client” all the information about how the introduction of ML has changed the internal processes of the involved actors. Then, moving to micro-level codes, we grouped all the information about the impact of ML innovation on employees’ skillset under the label “skills_requirements”.

Finally, the summary scheme encompassing all the codes has been analyzed in the light of the theoretical domains outlined in Table 4 (see section 4) to contribute to the advancement of knowledge on the subject. This comparison allowed us to identify new domains in the analyzed setting, as well as to explain the relationships among all the identified domains.

4. Theoretically-derived building blocks of VCC in a ML-enabled business context

The ML’s revolutionary potential lies in the creation of intelligent and communicative systems, which enable the interaction between human and machine intelligence through networking (Schwab, 2017; Gourisaria *et al.*, 2021). ML can automatically identify patterns by analyzing huge volumes of data–i.e. a data lake–, without the need to define them *a priori* and uses these patterns to predict future events or to prescribe decisions in uncertain conditions. Due to its learning capabilities, ML can use previous results to progressively improve predictions and prescriptions. ML allows the digitalization of the entire production process, by equipping traditional industrial machinery and products with sensors, microprocessors and software for data collection and analysis to complement physical processes with digital ones. This way it is possible to create synergies between products and services, monitor physical processes and decentralize decision-making, thus improving flexibility, productivity and competitiveness (Liao *et al.*, 2017; Porter and Heppelmann, 2014). That is to say that ML enables companies to explicit the tacit knowledge embedded in business processes, as well as in the direct and indirect interactions companies have with the other actors within their ecosystem (Crupi *et al.*, 2022; Murphy, 2012).

Scholars unanimously point out that servitization implies that companies adopt a service-oriented business model instead of a product-centric one (Frank *et al.*, 2019b) and that this determines a shift from a concept of “value in exchange” to a concept of “value in use” (Vargo *et al.*, 2008; Vargo and Lusch, 2004) i.e. coming from the clients’ utilization of the PSS (Edvardsson *et al.*, 2011). Similarly, other scholars intend value as uniquely and phenomenologically determined by the beneficiary (Grönroos, 2011; Uden and del Vecchio, 2018). Therefore, value does not merely derive from owning a product, but it stems from the benefits clients attain by using the product (Smith *et al.*, 2014). Consistently, the focus of manufacturing companies should move from the means for achieving such benefits (i.e. the product) to the benefits themselves (Cook *et al.*, 2006).

ML’s cognitive ability has caused a shift from merely describing how consumers behave to predicting and even trying to influence that behavior (Canhoto and Clear, 2020). Since ML enables a continuous interaction between a firm and its customers, firms are no more restricted to offering value propositions only but have an unprecedented opportunity to influence their customers’ value creation drivers directly and actively (Grönroos, 2011). Consistently, the *value driver* significantly changes, as companies can not only acquire knowledge on the benefits clients expect from using the PSS but can also exploit ML's learning capabilities to anticipate clients' needs and enrich their PSS with the desired benefits, even before they become explicit needs.

The VCC logic does not focus on the exchange of tangible resources (i.e. goods), but on the application of intangible resources, such as knowledge and skills, upon tangible ones, to generate value (Vargo *et al.*, 2008). The relevant *resources used* in VCC are thus invisible, and sometimes they are embedded in goods (Vargo and Lusch, 2004). The fundamental basis of exchange is the PSS (Uden and del Vecchio, 2018), which is a vehicle for enabling access to the benefits stemming from the firm's competencies (Vargo *et al.*, 2008). Therefore, in a ML-enabled co-creation environment, algorithms constitute an operant resource that derives from the exploitation of the existing skills and knowledge embedded in people working within an organization. Additionally, the learning capabilities of ML algorithms foster the creation of brand-new knowledge, thus activating a virtuous cycle of operant resource generation and development.

The introduction of ML algorithms has the potential to revolutionize the *role of goods* by enabling a bi-directional flow of knowledge. On the one hand, goods still represent the vehicle through which manufacturers transfer their skills and knowledge to the beneficiary. On the other, goods become a means through which manufacturer collects data that can be turned into new knowledge to foster VCC. That is to say that VCC takes place in networks, within which all actors "integrate resources and engage in service exchange", and value propositions stem from the interaction between all actors operating within an institutional arrangement (Vargo and Lusch, 2016). The value creator therefore should be referred to as a multiplicity of actors within the economic and social environment, always including the beneficiary (Uden and del Vecchio, 2018).

Regarding the *role of value co-creators*, different and partially contrasting opinions emerge from the literature. Following Vargo and Lusch (2008, 2016), whether it is possible to say that all the beneficiaries are also value co-creators, it is not possible to assume vice versa as automatically true. That is to say that the firm is always considered as an active participant in VCC, which begins with the PSS design and realization, and it ends with the customer's use of the PSS itself to acquire the desired benefits. Contrastively, Grönroos (2011) conceives value only as "value in use", thus excluding production activities from the VCC process. This leads to assuming that, while the customer always creates value, the company can become a full-fledged value co-creator only when it directly interacts with its customers.

Further, Xie *et al.* (2016) point out that when introducing Industry 4.0 technologies, there happens a coincidence between the value co-creator and the value beneficiary. This conception can be applied also to a ML-enabled environment. Since the primary resource is represented by the knowledge that can be extracted from data, all the actors that interact within the ecosystem and share data to be processed through a ML algorithm become simultaneously participants in VCC and beneficiaries of the co-created value.

The *purpose of the co-created value* is to "increase adaptability, survivability, and system well-being through service (applied knowledge and skills) of others" (Vargo *et al.*, 2008, p. 148). Scholars and practitioners amply recognize that ML has the potential to enhance decision-making processes, lower product and service costs, speed up business processes, offer a better service level to customers, as well as to foster industrial innovation (Lee and Shin, 2020; Teece, 2017; Urbinati *et al.*, 2019). That is to say that ML can significantly influence the type and scope of co-created value, allowing us to translate the general axioms of "adaptability, survivability, and system well-being" into more tangible dimensions. ML can facilitate the process of knowledge creation, management, development and sharing both within and outside the organization (López-Cabarcos *et al.*, 2020), which constitutes a crucial ability in the digital era. With ML technologies, therefore, companies can explicit the tacit knowledge embedded in business processes and interactions with the other actors operating within its ecosystem, thus innovating their business model according to a servitization perspective (Naik *et al.*, 2020; Opresnik and Taisch, 2015).

Stemming from the above, two main considerations emerge. First, *measuring the co-created value* implies determining the level to which this purpose is achieved in each of these dimensions from the perspective of the beneficiary (Uden and del Vecchio, 2018). To do so, it is necessary to determine a new set of performance measures that considers at least two perspectives: one regarding the resource managers (i.e. the service provider) and the other one concerning the customers. Second, there is not a clear distinction between the different phases of the *VCC process*, which can thus be conceived as a system of activities carried out by the different actors in a concomitant and integrated way, rather than in a temporal sequence.

Finally, Vargo *et al.* (2008, p. 148) underline that a crucial premise of the Service-Dominant Logic is that "all social and economic actors are resource integrators". Consistently, VCC logic springs from the combination of the energies emerging from the firm (i.e. technologies, organization, or employees), from its stakeholders (i.e. customers, shareholders) and from the whole ecosystem (i.e. social, ecological, or governmental actors) (Prahalad and Ramaswamy, 2004). These energies originate endogenous and exogenous forces that contribute to shaping the specific configuration the company adopts in organizing its VCC process. Specifically, the VCC perspective emphasizes that even if the exogenous forces are generally considered uncontrollable, they are fully involved and integrated with the VCC process together with other elements of the service system (Lusch and Vargo, 2014). This is aligned with the pillars of the configuration approach, according to which a specific configuration is the result of the interaction of the above mentioned endogenous and exogenous forces, combined with the peculiarities of the firm itself (Gersick, 1991).

Table 4 shows the theoretically derived domains of a possible configuration of VCC in ML-enabled context, and it constitutes the static part of a configuration inquiry. Since when analyzing a configuration, possible relationships between variables are not acknowledged (Gerdin, 2005), the static analysis needs to be complemented with a dynamic perspective.

Table 4. Value co-creation domains in a Machine Learning-enabled context

Domain	*Definition*
VCC driver	Expected benefits the customer can gain from using the digitally-enabled PSS, and the needs that can be predicted via ML before they become explicit
Resource used	Intangible resources, such as existing skills and knowledge embedded in goods, and brand-new knowledge that ML algorithms and related software are able to create within a virtuous cycle of resource generation and development
Role of goods	Bi-directional vehicles of resources exchanges, through which the manufacturers transfer their skills and knowledge to the customer and collect data to be turned into new knowledge
Role of value co-creators	All the actors that interact within the ecosystem by sharing data to be processed via ML become simultaneously value co-creators and beneficiaries of the co-created value
Purpose and measurement of co-created value	ML helps in translating the concepts of "adaptability, survivability and system well-being" in terms of more tangible dimensions that can be measured to express the degree to which such purposes have been achieved
Process of VCC	Set of concurrent activities to be analyzed dynamically according to at least two perspectives: that of the manufacturer and that of the customers
Contingent forces	Exogenous and endogenous forces that lead to the adoption of a specific configuration among the finite number of possible ones

Source(s): Author's own creation

5. Empirical research findings

This section reports the results of the Dilorean case study. By analyzing the results, it is possible to enrich the definitions contained in the theoretical framework proposed in Table 4 with new and more detailed elements that contribute to extending our knowledge of how VCC manifests itself in a ML-enabled real-life setting. Further, the analyzed case allowed researchers to understand the dynamic relationships among the different configuration's domains.

5.1 Value co-creation driver

Interviewees unanimously consider the benefits clients can obtain from the use of the PSS as the fundamental value driver. Consistently, Dilorean adopts a reactive posture toward its clients' desires, and it uses ML's predictive and prescriptive capabilities to fulfill them.

> Our credo is "for you with you", and every action we take to develop the company is intended toward the client. We do everything we can to meet our clients' needs. [D01]

The company's will to propose a PSS able to adequately respond to its clients' needs activates a virtuous cycle of knowledge generation and sharing that stimulates the adoption of a proactive rather than merely reactive behavior. Dilorean takes advantage of the knowledge that emerged from its clients' current use of the PSS to generate new knowledge that allows the company to anticipate clients' potential needs (Canhoto and Clear, 2020). In such a scenario, the potentialities of ML technologies acted as enablers of the company's proactivity. Dilorean translated many different needs stemming from different individual clients and systematized them to give rise to a single PSS able to provide benefits for an entire ecosystem of actors, which included Dilorean itself.

> Our clients desired to automate as much as possible the functioning of the machinery, taking this responsibility away from the laborers that do not show strong motivation in pursuing the best levels of efficiency and effectiveness in production. To precisely fulfill this goal, we started to install sensors on our machines. [D02]

> What was Dilorean's strength? It was to take the different clients' outbreaks and bring them together in a single system that could have also provided us with advantageous outcomes [D01]

These results suggest that ML expands what we identified as the VCC drivers within the proposed theoretical framework. A relevant driver for VCC is also represented by the benefits the manufacturer expects for himself from the customer's use of the PSS. ML was introduced at the beginning to enhance the product's performance in clients' favor. ML's intrinsically interactive nature (Naeem and Di Maria, 2021) has resulted in advantages in favor of the entire ecosystem, including the manufacturer.

5.2 Resource used in value co-creation

Interviewees point out that the Gold System encloses all the knowledge the company has acquired overtime on the reference industry, its production processes, its products and machines' design and functioning. Moreover, clients' use of the Gold System gives the company access to huge amounts of data regarding machines' functioning and performance. This data is continuously stored in a single repository, namely a data lake, so that ML enables a virtuous cycle of knowledge generation and sharing among the manufacturer, its clients and the entire ecosystem in which they are embedded (Urbinati *et al.*, 2019). Stemming from the interviews, it was possible to unfold the domain of resource used into three distinct knowledge flows.

First, data flowing from the clients' use of the Gold System give the manufacturer a more granular understanding of their use of the PSS. This way Dilorean can provide its clients with personalized diagnostic and predictive tools that support their production processes, as well as dynamic and interactive reports on their performance.

> Every second Gold records about a thousand of data . . . can you imagine what a huge amount of data we can access every day? We use this data to develop diagnostic, predictive and prescriptive algorithms aimed at supporting our clients in doing their business efficiently and effectively. [D02]

Second, the data collected from each client that is networked and integrated into the data lake serves a wide range of scopes. By performing advanced analyses on the entire data lake, the knowledge shared by the whole ecosystem of clients constitutes the basis to generate new knowledge for the benefit of both Dilorean and the clients themselves.

> Data represents a broad-spectrum source of knowledge. Our algorithms process that data to manage and guide clients during their activities, to guarantee a fast and effective intervention in case of a machine malfunctioning, but also to potentially demonstrate when they do not comply with our prescriptions and act accordingly. Data fuels also the R&D processes, not just the continuous improvement of the service we provide to clients. Thanks to analysis performed on the data lake, we now have four different product lines, but this is just the tip of the iceberg. [D02]

> Gold has such a potential that we founded an entire business unit specifically dedicated to the development of its functionalities and to exploit the data for customer care purposes. [D03]

Third, the knowledge-sharing process expands to involve also the client's ecosystem. Clients sometimes ask Dilorean to integrate part of the information deriving from the analyses performed on the data lake with the data stemming from their management information system. This way, clients can also benefit from a better relationship with the other actors along their value chain.

> Some clients wanted to integrate the data and information Gold provides them with their management information systems, to create synergies with their suppliers, clients, or business partners. To answer this need, we created ad hoc interfaces that run on our clients' devices. [D01]

The case confirmed that knowledge is the most relevant resource used within a VCC process (Vargo *et al.*, 2008) and highlighted that this resource is made available to and exploited by the multiplicity of actors that intervene in VCC processes. As compared to the proposed theoretical framework, Dilorean's case allowed us to identify how knowledge is used, created and shared within a VCC process by pointing out three distinct knowledge flows that run not only between the manufacturer and the client and within the manufacturer's ecosystem but also across all the different clients' ecosystems.

5.3 Role of goods in value co-creation

The proposed theoretical framework highlights that the use of ML algorithms on sensor data collected from the machines' functioning creates an even tighter connection between tangible and intangible resources, thus affecting the role of goods in VCC. Interviewees point out that the knowledge generated using ML on sensors' data allows for activating continuous monitoring of the machinery's functioning.

> Sensors provide us with a continuous flow of data on the functioning of every machine we sold in each corner of the globe. We can monitor in real-time what's happening to every machine through a dashboard that signals when a machine is not functioning at its optimal level of efficiency, and we use this data to inform the client that there is something wrong. This is a win-win opportunity because the client can timely intervene to reactivate the machine's optimal functioning, and we can record every second of production processes to improve our products. [D01]

> We first digitalized maintenance sheets by connecting them to the actual production data to create personalized warnings that suggest to each client the best time to perform the maintenance, the tools

> he needs to complete the task, and specific instructions on how to perform the task. We shifted from an 'emergencyandgo' approach to maintenance to real predictive assistance. Now we can predict damage way before it happens: we see that a machine's functioning is 0,5% lower than its optimal level. Well, we can identify exactly where the problem is and send the client a warning to fix the problem before it can cause any production loss. [D03]

This constant exchange of data among the manufacturer and the entire ecosystem of clients makes it possible for the data lake to be continuously fed, but also to expand its scope as the data it contains can be used to further develop the PSS. Specifically, the manufacturer can use this knowledge heritage to improve the offered products, develop new ones, as well as to enrich its value proposition by offering new services.

> The data is king. We don't simply save production data from our clients, but we started to collect data also from the warnings the system generates, and from the solutions we provided for those warnings. Our current challenge is to use these data to develop a troubleshooting tool that will lead to completely automating machinery's maintenance and repair. [D02]

From the analyzed case, therefore, it seems to emerge that the role of goods significantly expands in a ML-enabled real-life setting. Goods do not run out their role with the resources exchange, but they contribute to enriching the purpose of VCC. First, clients' use of the PSS allows the data lake to be continuously fed with new knowledge that can be re-transferred to the clients in the form of continuous monitoring and process optimization. Second, goods include a knowledge heritage that constitutes the fundamental input to the development of new PSS.

5.4 Role of value co-creators

Dilorean developed the services embedded in the PSS (i.e. the Gold System) by exploiting the data lake fed by all its clients. Interviewees point out that this continuous exchange of data allows Dilorean and its clients to benefit from dynamic and constantly updated reports on machinery's performance. Moreover, each client takes advantage of the insights stemming from the analyses performed on the data collected from all Dilorean's clients.

> The system collects the solutions proposed to each client, so it can learn from multiple sources and apply probabilistic calculations to suggest the most appropriate solution (how many times this tip has proved effective for others with the same problem?). [D02]

Dilorean too benefits from the co-created value because the PSS becomes the "Trojan horse" that enables to access all the data generated by the clients' operations, which can be exploited for multiple purposes: to improve customer service levels, continuously update products and services to be offered to current and potential clients, to design new products and to create new business areas.

> The opportunity to see what's happening in each plant, and to access real-time data and reports allows us to intervene in the machines' design and increase their average functioning speed. It's a "win-win" situation, where the clients' time decreases and I sell more services so that the two of us make more money. [D01]

Literature underlines that digital technologies create a coincidence between value co-creators and value beneficiaries (Xie *et al.*, 2016). The analyzed case makes it possible to highlight that value co-creators assume diverse roles depending on the different impacts they can have in the knowledge generation process. Manufacturers have an integrated and systemic view of all the collected data (i.e. the data lake) and assume a managerial role in the VCC process, as they can decide what data should be collected, and for what purposes to run ML algorithms.

> The system specifically dictates how, when and with what tools to apply the maintenance sheet. If the client does not follow the instructions and the machine breaks, he is to blame, and we are not obliged to repair the machine in warranty. [D03]

Customers instead have limited power in deciding the scope of the analyses since they just continuously feed the data lake, into which also flows all the data deriving from all the other companies with which the manufacturer interacts. Indeed, clients participate in the VCC process as co-creators (Vargo and Lusch, 2008, 2016) only if they comply with the accountability parameters dictated by the prescriptive logic of the ML. Otherwise, they still provide useful data, but they can no longer benefit from the systemic logic between product and service and take advantage just of the product instead of the entire PSS.

To overcome potential concerns about data security and confidentiality, Dilorean has outsourced the cybersecurity management to specialized firms and created a data lake that is "closed in entry", where clients can only browse the reports provided by Dilorean, without directly accessing the original data.

> The database is closed within the Gold System. We give the clients interfaces from which they can interact with the results of the analysis Gold performs. Clients can't access the database matrix. They can browse the extrapolations and navigate in dynamic reporting systems but without accessing the underlying data. [D02]

> The machine we sell has a simple dashboard with no intelligence or the necessary computing capacity because it is not the machine's job to self-learn. [D03]

This suggests that the way in which the system is designed (i.e. whether it consists in a closed in entry or an open access data lake) contributes to increasing (or reducing) the imbalance in knowledge management power between the involved actors.

Stemming from interviewees' responses it is possible to argue that assuming the role of data manager and "data protector" gives an "ownership right" on the knowledge that is shared and created among the actors of the VCC process, thus determining who is the most powerful one.

Summarizing, we can identify three different factors that determine an imbalance in knowledge management power among value co-creators that favor the manufacturer against the clients. First, the use of ML stimulates the development of a PSS able to become the "Trojan horse" that allows the manufacturer to access and own unprecedented volumes of data that can be exploited for multiple purposes. Second, exclusive access to the data gives the manufacturers an integrated and systemic view of the data lake, thus favoring them in assuming a managerial role. Third, the prescriptive logic of ML not only acts as a facilitator, by enhancing clients' business processes, but also as a compelling force for customers that limit their power by imposing them specific practices.

5.5 Value co-creation process in a ML environment

The interviewees' opinions confirm that ML dramatically impacted the process of VCC. The opportunity to exploit a data lake that is constantly fed by the entire ecosystem of clients for a wide range of purposes implies that value is continuously created and co-created (Xie *et al.*, 2016), according to a scheme that cannot be reduced to a sequence or a cycle of events. Rather, all the actors involved in VCC act and interact in a concomitant and integrated way.

> The term ML holds all the journey toward the development of the Gold System. I can't say what comes first and what follows . . . In the beginning, we needed an initial dataset to develop and run our experimental ML algorithm, but now we can talk about a continuous work of collection, analysis and interaction with our clients. This journey consists of three main activities: sensoring, networking and analysis. Via sensors, we collect data on production process advancement, resource absorption, consumption and even the weather conditions that can impact production processes. These data are connected in a single data lake that is exploited to develop advanced algorithms able to support us and our clients to continuously improve our respective activities. [D02]

5.6 Role changes in a ML-enabled value co-creation environment

The potentialities brought by ML are not limited to the development of the PSS, the creation of new business areas, or the innovation of the existing ones (Wagire *et al.*, 2020; Nazarov and Klarin, 2020). Interviews suggest that ML also has a significant impact on the organizational dimensions of both Dilorean and its clients, by requiring new skills and competencies.

> The entire company is changing. We founded a digital innovation department, so we need people with specific competencies in data analysis. When you have data and you know what its potential is, you also understand where your business can go and how to expand it more effectively. [D01]

The centrality data assumes for the firm's value proposition is the most significant driver for changing roles within the manufacturer. Dilorean is looking for a new set of competencies even in machine design, in terms of advanced capabilities in extracting value from the data lake and in supporting the company's decision-making processes.

> Until a few years ago our core business was machines' design, now the most relevant challenge is to analyze data and to develop prescriptive and predictive algorithms to offer the best solutions to our clients' problems. We need to change substantially the kind of people we employ. [D01]

> We do not need more people, but different people with a completely different approach to data. Machine designers are accustomed to machine software management, but they are not familiar with data analytics software. Well, we need people that are also well conversant with data analytics technologies because communicating with them is way much easier. We give them a few information as input, and they elaborate on machines' data to turn them into exactly the output we asked for. [D02]

The change ML requires in the manufacturer's skills and competencies also reflects on the organizational structure of the client.

> Once, only the laborer knew how to run the machine. He was like a guru, without whom no production process could have been run. With ML-enriched machines, no guru is needed because the machine automatically sets up and functions and can be remotely monitored. The client needs a different kind of laborer, able to interact with the dashboard to run and maintain the machine. [D01]

The case suggests considering another relevant domain, which refers to how ML impacts the organizational structures of value co-creators. Results highlight that the use of ML puts data collection and analysis at the very center of manufacturers' value proposition, thus requiring a substantive change in the role of product designers. These employees must possess or acquire new competencies, not simply related to product engineering but also related to advanced data analysis to effectively support the company's digital innovation journey. Simultaneously, new competencies are also required for the clients' operational personnel. The use of ML algorithms requires the operator to have an increasing ability to interact with the software, rather than to manage machines' functioning.

5.7 Purpose and measurement of value co-creation via ML

Regarding the purpose and measurement of VCC, literature generally refers to the "adaptability, survivability and system well-being" (Vargo *et al.*, 2008, p. 148). By investigating VCC via ML in a real-life setting, it is possible to translate this general axiom into more concrete performance dimensions through which one can measure to what extent value co-creators have reached the VCC purpose. The analyzed case allowed us to identify operational, strategic and financial dimensions into which the general purpose of VCC can be declined for both the manufacturer and its clients.

First and foremost, the opportunity to collect data on machines' functioning contributes to increasing the manufacturer's cost-effectiveness (Lee and Shin, 2020; Teece, 2017; Urbinati *et al.*, 2019). Machines are designed and realized by selecting the most appropriate components for their desired performance, thus avoiding expensive oversizing.

> Our designers used to be cautious when choosing the engine to install on the machines . . . I mean . . . what matters if it has too much power for the speed it should go? At least it won't break at its maximum speed! Well, now we can see if a specific machine is under-utilized in its current setting so we can save costs by installing a smaller (and cheaper) engine, suitable for its target speed. [D02]

Moreover, predictive maintenance and troubleshooting tools allow a significant reduction in the number and costs of repairing interventions borne by the manufacturer during the warranty period.

> One can not only anticipate the client's problem through a predictive diagnostic and maintenance system, but with an automated troubleshooting tool, you can provide the client with a set of possible solutions without even meeting him. Can you imagine how many costs you can save? [D03]

Clients too can save costs and maximize performance by using the ML-enabled PSS. The same tools used to automatically schedule maintenance, diagnose malfunctioning causes and propose effective solutions to them, dramatically reduce machine downtime and allow clients to take full advantage of its productive capacity.

> Every machine downtime can cost our clients between 15.000 to 16.000 Euros. The thing is that 70% . . . maybe 80% of these downtimes are disposable through timely maintenance and early diagnosis. The tools we developed are an epochal change! [D02]

Further, automating the machine's functioning via the ML algorithm impacts both clients' and Dilorean's performance. Clients can overcome the bias related to laborers' prudential behavior in running the machines, as they automatically reach their optimal speed level. This automation minimizes the opportunity costs related to machines' functioning undersize, reduces maintenance and machines' downtime costs and maximizes revenues by constantly pushing machines' productivity.

> The Gold System analyzes historical data on machines' functioning to automatically set their target speed. Then, the system installed on each machine monitors all the process variables and, as long as they stay within an efficiency threshold, the machine automatically pushes its target speed limit. The last reached target speed represents the starting speed of each production cycle. [D02]

Simultaneously, the Gold System had tangible effects on Dilorean's financial performance, in terms of revenue increase, financial results and company's growth. Dilorean, indeed, has founded a business unit specifically dedicated to the Gold System, namely ProGold, and a digital innovation department, thus increasing personnel. Although the Gold System has not determined a remarkable increase in the machines' sale price, as it is limited to the 1.8% of their final price, it has stimulated the development of new products with consequent enlargement of the client base.

> If we compare the Gold System's price with that of the entire machinery, its financial impact is obviously very low. However, Gold has high margins, as its costs are limited to the initial investment needed to develop the algorithm and some costs related to the software's updates. [D01]

> The financial perspective does not consider the strategic relevance of the Gold System in the design and development of new products. We now have four different lines of products, just because of the analyses we performed on our client's data via Gold. Again, think about ProGold . . . a brand-new business unit, with a dedicated employee, and that is further growing. [D02]

Introducing ML in VCC also impacts the relationship between Dilorean and its clients. That is to say that Dilorean can count on higher client satisfaction and loyalty, due to the ability of the Gold System in preventing machines' downtime, which makes the clients not only more profitable but also more capable of satisfying their reference market needs.

> Perhaps the term customers' loyalty cannot express how we relate with them . . . we have a nearly symbiotic relationship with our clients, and they have now become our best salespeople. Since the first time they tried Gold, they literally fell in love with it! [D03]

> There was a laborer that said, "Gold is the first colleague I greet every morning, because I take a look to the dashboard and I can see if overnight something happened, so I can figure out whether I must expect some bad surprise during the day". I mean . . . that says it all! [D01]

Even the high level of service Dilorean can ensure to its clients represents a direct consequence of the adoption of ML. The effectiveness of diagnostic and predictive tools provided via the Gold System benefits from the opportunity to analyze an entire data lake that is fed by Dilorean's ecosystem of clients. Each client takes advantage of the wider network of relationships within which Dilorean constitutes the focal point.

> The service we provide is like a child that grows up under the responsibility of an entire community of parents, instead of just two. Gold offers personalized solutions to each client, but these solutions derive from the analyses we perform on the data we collect from all our clients, and from all the solutions we propose them over time. [D02]

5.8 The impact of contingent forces on value co-creation

Literature underlines that a set of endogenous and exogenous forces can affect the choice of a specific VCC process configuration among the number of possible ones (Gersick, 1991).

Dilorean's case allowed researchers to identify some of these forces. The Dilorean' mission "For you. With you." and the related will to answer the call for an improvement of production processes expressed by its clients was the primary force that encouraged the use of ML.

> Our clients wanted a machine able to guide the laborer instead of one that required the presence of an operator to properly function. Their satisfaction is our main goal, so we started to brainstorm around Industry 4.0 solutions to turn that input into valuable ideas and systems. [D02]

> It's now very common to hear about Smart technologies and Industry 4.0, mainly because of the government incentives, but we started way before this phenomenon became popular. In 2005 we started to receive inputs from our clients. Accordingly, we launched different stand-alone initiatives. Our main strength was to combine all these initiatives within a single system: Gold. [D01]

Although Dilorean proactively adopted digital technologies to enrich its products, clients' awareness about the potentials and limits of digital technologies, i.e. their digital maturity, in some cases hindered VCC.

> Before Industry 4.0 became a trend, the use of algorithms was very difficult. When we first installed sensors and started data collection, some clients did not even have a Wi-Fi connection, so the algorithms could not work. When internet connection ceased to be a struggle, the clients' main concern shifted to data security. It is still difficult sometimes to convince the client that we cannot access all their sensitive or confidential data on their customers, products, or processes. [D03]

Finally, the leadership style of Dilorean's shareholders endogenously fostered a digitally enabled value proposition.

> In the middle of our digital revolution, we were acquired by a large firm. Luckily, the new owner let us do whatever it takes to meet our clients' needs as long as we obtained positive results. [D01]

> All the people here strongly believed in that digitalization journey, so we decided to keep going on that path and now we are very proud of the results we reached, and even more enthusiastic to discover what the future will bring over. [D02]

Dilorean, therefore, adopted a pioneering posture toward digital innovation, that finds its roots in the company's ability to interact with the ecosystem in which it operates, rather than in attempting to mimic other organizations' responses to a change within the institutional environment or to market trends.

In sum, results show that the vision and the mission of the manufacturer can act as a major endogenous force in stimulating business model innovation initiatives according to a digital servitization perspective. Though companies tend to adopt strategic initiatives that are consistent with the principles underlying the business, the strength of this conformance is substantially influenced by the leadership style.

We observed that the manufacturer started its digital innovation journey way before Industry 4.0 became a trend in almost every sector. However, the increasing debate about the potentialities of Industry 4.0 technologies within the business community has made clients more willing to explore such opportunities, thus allowing the development of a ML-enabled PSS. Therefore, the spread of the Industry 4.0 acted as an exogenous force that has fostered such an alignment between manufacturer and clients' digital maturity.

5.9 The dynamic interaction between the domains

In Section 4 we identified seven domains to be considered when analyzing a ML-enabled VCC configuration. These domains constitute specific features of a configuration that become meaningful only when analyzed according to a dynamic approach, i.e. when analyzing how these domains interact to create order within an organization (Dess *et al.*, 1993; Miller, 1996). The study of Dilorean's case allowed the researchers to integrate the theoretically derived framework with new and more detailed elements regarding the already identified domains but also to detect a new domain, related to the changes ML requires in value co-creators. Accordingly, in the present section we propose a revision of the domains resulting from the literature review combined with the case study (see Table 5).

The case study has also allowed to shed light on the dynamic interactions among the different configuration's domains. In this respect, it seems to emerge that the role of goods, the resources used and the role of value co-creators dynamically influence each other to shape many different purposes of the co-created value, and in turn affect the drivers of VCC. The research highlighted that value co-creators have different roles in VCC depending on the degree of power they have in managing the resource used (i.e. mainly the knowledge that is created and shared within the ecosystem). Stemming from this, it is possible to point out that the most powerful co-creator, namely the manufacturer, chooses the VCC drivers to be followed and decides what data should be collected, and for what purposes ML algorithms run. In parallel, clients do not directly promote innovation. Clients are pleased when the manufacturer fulfills the benefits they expect, and even more when they can acquire benefits they hadn't thought about yet.

At least at the beginning of a VCC initiative via ML, there is a strong imbalance between the knowledge management power of the involved actors. Clients' expected and predictable benefits constitute the most influential driver, and clients act more as value beneficiaries rather than full-fledged value co-creators. To become value co-creators, clients need to conform to the requirements imposed by the prescriptive logic of ML but also to be at least in line with the manufacturer's digital maturity level.

In a ML-enabled VCC process, the number of actors to be considered as value co-creators and their respective role is affected also by the resources used and by the role of goods assume as primary means of knowledge sharing and creation. These dynamic interactions overcome the boundaries of the relationship between the client and the manufacturer. In fact, it expands to consider all the knowledge that emerges from the relationships within the manufacturer's

Domain	Definition	Findings
VCC driver	Expected benefits the customer can gain from using the digitally-enabled PSS, and the needs that can be predicted via ML before they become explicit	Expected and predictable benefits that the manufacturer, the customer and the entire ecosystem can gain from using the digitally-enabled PSS
Resource used	Intangible resources, such as existing skills and knowledge embedded in goods, and brand-new knowledge that ML algorithms and related software are able to create within a virtuous cycle of resource generation and development	Knowledge embedded in goods that ML algorithms and related software are able to create and share between the manufacturer and client, within the manufacturer's ecosystem, and across the manufacturer's ecosystem and the clients' one
Role of goods	Bi-directional vehicles of resources exchanges, through which the manufacturers transfer their skills and knowledge to the customer and collect data to be turned into new knowledge	Multi-directional vehicles of resources exchanges, that involve a larger number of value co-creators and beneficiaries that includes also new player from outside
Role of value co-creators	All the actors that interact within the ecosystem by sharing data to be processed via ML become simultaneously value co-creators and beneficiaries of the co-created value	Each actor that interacts within the ecosystem differently contribute to VCC basing on their degree of power in knowledge management, which depends on the digital maturity and the accountability related to the ML logic
Role changes (new domain)	–	Digital servitization via ML imposes to each co-creator to acquire new skills and competencies, and to redefine the way in which they relate to each other
Purpose and measurement of co-created value	ML helps in translating the concepts of "adaptability, survivability and system well-being" in terms of more tangible dimensions that can be measured to express the degree to which such purposes have been achieved	ML helps the manufacturer in: (1) avoiding oversizing matters; (2) reducing the costs of repairing interventions; (3) constituting new SBUs, such as the digital innovation department; (4) promoting higher client satisfaction and loyalty ML helps the clients in: (1) reducing machines' downtime; (2) maximizing productive capacity levels; (3) overcoming labors' related biases; (4) benefiting from networked information and knowledge
Process of VCC	Set of concurrent activities to be analyzed dynamically according to at least two perspectives: that of the manufacturer and that of the customers	Set of concurrent activities to be analyzed dynamically according to at least two perspectives: that of the manufacturer and that of the customers
Contingent forces	Exogenous and endogenous forces that lead to the adoption of a specific configuration among the finite number of possible ones	Exogenous forces: (1) Availability of technological advancements Endogenous forces: (1) manufacturer's mission and vision; (2) manufacturer's leadership style; (3) digital maturity of clients and of ecosystem's actors

Source(s): Author's own creation

Table 5. Revised value co-creation domains in a Machine Learning-enabled context

ecosystem, and also the knowledge that flows across the manufacturer's ecosystem and the clients' ones.

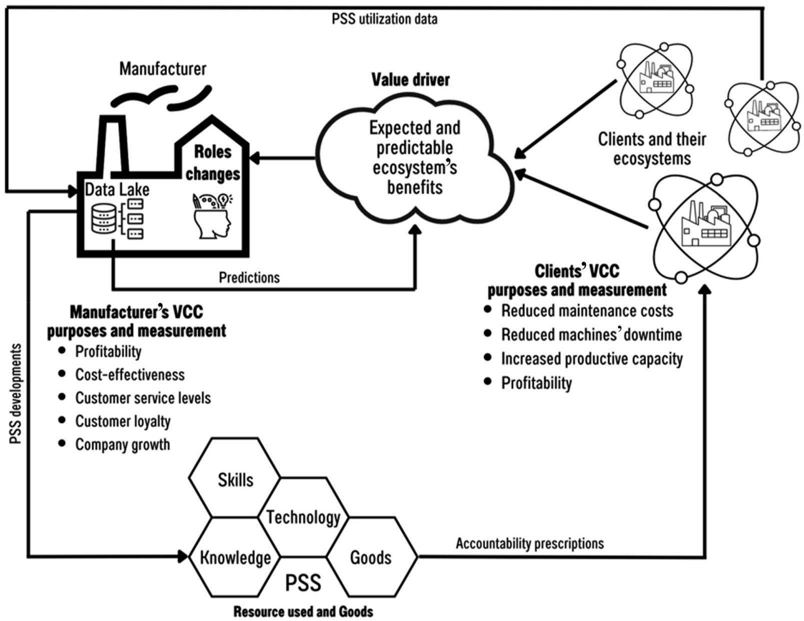
It emerges from the results that digital servitization via ML forces each co-creator to acquire new skills and competencies, and to redefine the way in which they relate to each other. This suggests that dynamic interactions of the domains do not just contribute to shaping the roles and the relationships among value co-creators, but also to re-shape the roles within the organization of each value co-creators (see Figure 1).

6. Discussion and conclusions

The aim of this paper was to understand how ML contribute to servitization processes, by specifically identifying the domains to be considered and how they interact when ML is used to shift from a product-oriented business model to a product-service-oriented one. To reach our aim, we based on configuration theory, and we proposed an interpretive framework that explains the configuration of a VCC process via ML.

According to the extant literature on servitization, VCC processes imply an interaction between two actors, which are identified as value co-creators: the manufacturer and the client (Vargo and Lusch, 2004; Vargo *et al.*, 2008; Lusch and Vargo, 2014; Uden and Del Vecchio, 2018). However, the co-created value is understood in terms of the benefits only clients attain by using the PSS (Edvardsson *et al.*, 2011; Grönroos, 2011; Smith *et al.*, 2014; Uden and del Vecchio, 2018), which constitute the fundamental value driver. Additionally, Xie *et al.* (2016) point out that when Industry 4.0 technologies are involved to carry on a servitization strategy, the respective roles of value co-creators and value beneficiaries tend to blur until they overlap.

The results of the present study suggest that the benefits the manufacturer expects from digital servitization can as well constitute a powerful driver for initiating a VCC process. The interactive nature of Industry 4.0 technologies (Naeem and Di Maria, 2021) that leads to the coincidence between the roles of value co-creators and value beneficiaries, shifts the



Source(s): Author's own creation

Figure 1.
The proposed interpretive framework

focus on the benefits of VCC from the client (proactive demand-pull approach) to the entire ecosystem of potential actors that can take advantage from the digital servitization strategy adopted by the manufacturer. Digitally-enabled PSS can not only establish an interactive relationship between the manufacturer and the client (López-Cabarcos *et al.*, 2020), or among the actors involved in the manufacturer's ecosystem. They can also foster the connection across different ecosystems, e.g. that of the manufacturer with the clients' ones.

The expansion of the concept of value beneficiary in VCC processes via digital servitization can be connected with another interesting phenomenon that extant literature on the topic seems to overlook. Specifically, scholars identify value co-creators as an ensemble of actors (namely, the manufacturer and its clients) that interact by sharing data and information, thus fueling a virtuous cycle of knowledge generation and sharing (Vargo and Lusch, 2004; Vargo *et al.*, 2008; Visvizi *et al.*, 2021). Academics underline that Industry 4.0 technologies, and specifically ML, have the potential to revolutionize companies' value creation and capture capabilities, by supporting decision-making processes and substantially changing the relationship between companies and their customers (Yoo *et al.*, 2010; Oluyisola *et al.*, 2022). Stemming from this, ML can be interpreted as a factor from which companies and their clients can only take advantage. Conversely, this study's results show that the predictive and prescriptive capabilities of ML (Murphy, 2012) act not just as facilitators of the relationship between manufacturer and clients, but also as compelling forces that impose accountability requirements on those who are involved in ML-enabled VCC.

The present study contributes to three main streams of literature. First, we contribute to the growing body of research on Industry 4.0 and its impact on business model innovation (Wagire *et al.*, 2020; Naeem and Di Maria, 2021). In this respect, our results highlight that the interactive nature of Industry 4.0 technologies favors the shift from a product-centric value proposition to a service-centric one. In this stream of literature, research is usually conducted through the lenses of the technology acceptance model (TAM) or the Technology-Organization-Environment (TOE) model (Chatterjee *et al.*, 2021; Srivastava *et al.*, 2022; Marrucci *et al.*, 2023; Grooss *et al.*, 2022). Nevertheless, scholars report a lack of contributions that investigate the different options and elements to be considered when firms start a digital transformation endeavor (Geum *et al.*, 2011; Hess *et al.*, 2016; Kohli and Melville, 2019). We adopted a different approach, namely configuration theory, which allowed us to shed light on the complexity of Industry 4.0 phenomenon, as it assumes a holistic perspective to understand what are the different options and elements to be considered and how order emerges from the dynamic interaction among these elements seen as a whole (Meyer *et al.*, 1993).

Second, our study adds to the research on VCC and digital servitization in manufacturing industries that calls for more contributions on how the opportunities brought by digital technologies can be exploited in VCC processes (Bolton *et al.*, 2018; Kohtamäki *et al.*, 2020; Reck and Fliaster, 2018; Troilo *et al.*, 2017; Uden and del Vecchio, 2018; Yoo *et al.*, 2010). In this respect, we propose an interpretive framework that identifies eight domains to be considered when analyzing a ML-enabled VCC configuration, thus shedding light on the different ways in which digital servitization can manifest itself.

Third, this research contributes to spread the interpretive potential of configuration theory by proposing new application settings (Short *et al.*, 2008), as that of digital servitization through ML.

From a practical standpoint, our results provide companies with a list of key elements that can be used for benchmarking purposes and for supporting organizations that intend to innovate their business model by adopting a digital servitization strategy via ML.

First, the manufacturer must be aware of its role as knowledge manager of the entire ecosystem of actors intervening in VCC, thus taking responsibility for the entire process.

This implies that the manufacturer is called into action to guarantee data security and to foster clients' alignment toward the adequate digital maturity level. Second, the introduction of digital technologies and the related business model innovation should be consistent with the underlying principles of the organization. Third, technology *per se* does not represent the main driver of digital servitization. Instead, technology constitutes a means through which the manufacturer defines a new business model able to consider all the potential benefits attainable for its advantage and also those attainable by all the other actors within its ecosystem. Finally, the adoption of a digital servitization strategy requires the manufacturer not only to develop skills and competencies in product engineering but also those related to advanced data analysis to effectively support the company's digital innovation journey.

This research also presents some limitations. When research is in its exploratory stage of development, a study that provides the theoretically derived domains of a VCC configuration and complements them with a case study is particularly suitable as it allows considering the uniqueness and richness of the considered firm. However, a single case study does not allow the identification of all the possible configurations that can emerge in real-life settings, so it represents the basis upon which typologies or taxonomies of all the possible configurations can be constructed. The identified domains could be used as inputs for statistical models aimed at identifying different configurations clusters, or at testing the validity of the relationships among these domains in different industries.

Moreover, since configurations are essentially subject to changes, so that the interdependencies among the domains can be better investigated by studying organizations over time, further research could adopt a longitudinal approach or realize a comparison among different cases. Finally, the investigation of the two perspectives considered in this study is based on the perceptions of the manufacturer who is one—albeit an important—actor in VCC processes. It would be interesting to further investigate the topic by complementing the analysis with the perspectives of other actors involved in VCC.

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About the authors

Claudia Presti (PhD) is a Junior Lecturer at the University of Pisa, Italy. Her research interests include studies on the relationship between digital technologies and management control, risk management and intellectual capital. She teaches Management Control and Performance Evaluation Systems at the University of Pisa. She is the author of several scientific papers in international journals and conference proceedings. Claudia Presti is the corresponding author and can be contacted at: claudia.presti@unipi.it

Federica De Santis (PhD) is an Associate Professor at the University of Pisa, Italy. Her research interests are intellectual capital, management accounting, management information systems and auditing. She teaches Financial Accounting, Big Data and Information Systems and Auditing, at the University of Pisa. She is the author of several scientific papers in international journals and conference proceedings.

Francesca Bernini (PhD) is an Associate Professor at the University of Pisa, Italy. Her research activity mainly regards accounting, business evaluation, ESG and business ethics. She teaches Business Economics, Financial Accounting and Strategic Evaluation at the University of Pisa. She is the author of several scientific papers in international journals and conference proceedings.