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How does artificial intelligence enable and enhance value co-creation in industrial markets? An exploratory case study in the healthcare ecosystem

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ABSTRACT

The technological revolution brought about from the digital transformation is dramatically reshaping how firms co-create value in B2B industrial markets. Among the many forms digital technologies can take, artificial intelligence is having the strongest pervasive impact. Relying upon empirical evidence stemming from a case study in the healthcare industry, our research aims at understanding how different types of artificial intelligence-based solutions support firms in co-creating value in B2B industrial markets. We advance an integrative framework having two iterative loops. The first iterative loop connects the technology service providers with the healthcare customers, showing how artificial intelligence-based customer-centric solutions are co-created through perceptive and responsive mechanisms; the second iterative loop connects the healthcare customers with the patients, enhancing operational practices through users' knowledge and resulting in better care and improved patient journey. Implications for theory and practice are discussed and ideas for future research are presented.

1. Introduction

Digital transformation is rapidly changing how industrial firms collaborate to create and capture value (Xie, Wu, Xiao, & Hu, 2016; Lenka, Parida, & Wincent, 2017; Teece, 2018; Appio, Frattini, Messeni Petruzzelli, & Neirotti, 2020). More precisely, this technological phenomenon refers to "the combined effects of several digital innovations bringing about novel actors (and actor constellations), structures, practices, values, and beliefs that change, threaten, replace or complement existing rules of the game within organizations, ecosystems, industries or fields" (Hinings and Gegenhuber, 2018, p. 55). This new digital paradigm is based on a vast array of enabling technologies, such as the Internet of Things, Additive Manufacturing, Big Data, Artificial Intelligence, Cloud Computing, Augmented and Virtual Reality, and Blockchain (Rindfleisch, O'Hern, & Sachdev, 2017). Among them, Artificial Intelligence (AI hereafter) is being the most widely implemented enabling technology in business-to-business (B2B) industrial markets for the execution of various corporate activities, such as sales, pricing, and management (Martínez-López & Casillas, 2013; Syam & Sharma, 2018). AI can offer to industrial firms also different types of market knowledge critical for B2B marketing, such as customer knowledge, user knowledge, and external market knowledge (Paschen, Kietzmann, & Kietzmann, 2019).

The wide application of AI by various leading global firms, such as IBM, Amazon, Microsoft, and Google, further emphasizes the great impact of this technology in B2B markets in the coming years. One of the key aspects AI brings about is the potential contribution to the processes of value co-creation between industrial partners. However, despite the extensive literature about value co-creation and digital technologies (e.g., Jaakkola & Hakanen, 2013; Kohtamäki & Rajala, 2016; Ramaswamy & Ozcan, 2018), to date scholars paid little attention to the specific role of AI. A recent systematic literature review explicitly confirms this literature gap by reporting that "there is no discussion […] on how AI or robots influence value co-creation in general" (Kaartemo & Helkkula, 2018, p. 216). Such a gap inevitably increases the complexity faced by scholars and B2B players in identifying which mechanisms and approaches are effective in order to achieve and manage value co-creation in AI-focused contexts.

Drawing on the assumptions that AI is a multifaceted concept (Huang & Rust, 2018) based on the exploitation of heterogeneous types of

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market knowledge (Paschen et al., 2019), the present article wants to contribute to the debate on the management of value co-creation in industrial markets in the digital transformation era. Accordingly, the leading research question follows: how does AI enable and enhance value co-creation in industrial markets? We performed qualitative exploratory research based on a case study in the healthcare industry, one of the main industrial markets in which AI has been massively implemented over the last few years (Topol, 2019). As a case study, we explored the role of Pieces Technologies, a US healthcare firm that provides AI-based solutions to gather and interpret patient information in real-time. We analyze how the application of the various types of AIs (i.e. mechanical, analytical, intuitive, empathetic) (Huang & Rust, 2018) supports the provider and customers of digital services in achieving value co-creation via perceptive and/or responsive mechanisms (Lenka et al., 2017).

Our article provides an original contribution to both the theories of AI-based value co-creation in industrial markets (Martínez-López & Casillas, 2013; Marcos-Cuevas, Nätti, Palo, & Baumann, 2016; Paschen et al., 2019; Frow, McColl-Kennedy, & Payne, 2016) and AI in services (Kaartemo & Helkkula, 2018; Huang & Rust, 2018). For these reasons, our study provides generalizable concepts that can be applied in other sectors thanks to the different use of AI-based solutions across different users involved in other B2B markets. AI-based solutions are forcing managers to rethink organizational structures and strategies in order to co-create value with their customers. Moreover, this is occurring in many other service industries such as tourism (Samara, Magnisalis, & Peristeras, 2020) and banking (Königstorfer & Thalmann, 2020; Christy, 1990). Finally, we generate an integrative framework showing how to connect the technology service providers' AI-based solutions (based on analytical, mechanical, intuitive, and empathetic intelligence), perceptive and responsive mechanisms for value co-creation, and the different types of market knowledge (customers' knowledge, users' knowledge, external market knowledge). The framework also highlights how these dynamics result in better care and an improved journey for patients. This framework supports scholars and practitioners in the healthcare industry.

2. Theoretical background

2.1. Value co-creation in the age of the digital transformation

Value co-creation "arises when both the supplier and the customer engage in an interdependent relationship" (Sheth, 2019, p. 2). This concept relates to value communication, appropriation, measurement, and representation (Corsaro, 2019). Scholars in industrial marketing adopted the most common research frameworks, such as the S-D logic, the resource-based view of the firm, and the transaction-costs economics to study value co-creation in B2B systems (Kohtamäki & Rajala, 2016; Frow et al., 2016). In practice, industrial partners have seven different relational options for establishing a co-creation link (Sheth, 2019): growing the customer business, regulation compliance, corporate social responsibility and triple bottom line, conscious capitalism, public policy reforms, breakthrough innovation, and public–private partnerships. Co-creation practices in industrial markets are reinforced by a widely shared objective and continued engagement in the collaborative actions of each involved actor in a common environment (Marcos-Cuevas et al., 2016; Frow et al., 2016). Also, third-parties, such as communities of users, can play a relevant role in support of the co-creation (Kohtamäki & Rajala, 2016). In a service-based perspective (Vargo & Lusch, 2004), technology service providers continuously need to look for opportunities to co-create value together with customers (Grönroos, 2011; Grönroos & Voima, 2013).

Industrial firms rapidly adapted their strategies, mission, and core competencies to quickly exploit the opportunities offered by the digital revolution (Cantù, Corsaro, & Snehota, 2012; Gulati & Soni, 2015; Teece, 2018; Appio et al., 2020). Digital technologies are a typical example of co-creation assets, by which providers and customers share the uncertainty of their interdependent business relationships (Ehret & Wirtz, 2018). Providers, for instance, can develop a physical co-creation asset, such as a cloud platform, or an intangible asset (e.g., software or tacit knowledge) in order to co-create value and increase their social capital with customers and other stakeholders within their industrial networks. These assets largely influence and redesign the stages of the customer/user journey and experience (Lemon & Verhoef, 2016; Følstad & Kvale, 2018). For instance, providers can use partner-owned touchpoints via mobile applications to orient customer choices during their purchasing journey (Lemon & Verhoef, 2016).

Digital technologies revolutionize in-depth how industries arrange their business networks to co-create value. A first central effect is an increasing relevance of the interactional creation of value, which essentially takes place via an interactive platform, "an agencial assemblage, composed of heterogeneous relations of artifacts, processes, interfaces, and persons, affording a multiplicity of interactive system-environments" (Ramaswamy & Ozcan, 2018, p. 198). In other words, in the current digital paradigm value co-creation can occur only by managing a very wide set of multi-level interactions entailing several industry stakeholders. A second effect of the wide spreading of digital technologies within business contexts relates to the set of key skills and capabilities required to industrial firms for value co-creation. In the digital transformation era, firms are forced to develop specific (intelligence, connective, and analytic) capabilities to enact two key mechanisms of value co-creation with their customers (Lenka et al., 2017): perceptive mechanisms, allowing providers to continuously auditing customers' operations, identifying, assessing, and building a customer-centric offer (e.g., by reducing process and resource use inefficiencies, rather than improving the overall performance); responsive mechanisms, clarifying how quickly and proactively providers react to their customers' changing and emerging needs (e.g., by implementing virtualized analytics and functionalities in the cloud).

2.2. AI and value co-creation in industrial markets

AI can be conceptualized as the computer's ability to perform tasks that resemble human thinking ability (Sabherwal & Becerra-Fernandez, 2011) despite human beings possess cognitive and emotional capabilities that mathematical schemes or algorithms cannot identically reproduce (Meskó, Hetényi, & Győrffy, 2018). These machines can plan specific actions precisely tailored for the customer experience, and monitor processes in real-time (e.g., via tablet or smartphone). However, these machines are not influenced by emotions and do not repeat the same mistakes made by human beings (Dartnall, 2013; Meskó et al., 2018; Huang & Rust, 2018). This last point deals with the issue of the exploitation of prior knowledge and experience by AI-based machines. Reactive machines make decisions without relying on 'memories' or even past experiences. This type of AI reacts directly to what it sees. Thus, these machines cannot do anything other than what they have been programmed for. Conversely, other types of AI machines with limited memory can partially rely on the past in their decision-making processes. The six building blocks of AI systems are structured data, unstructured data, pre-processes, main processes, the knowledge base of the firm, and the information outputs (Paschen et al., 2019).

Recent service management research shows that 'intelligence' in AI can be inflected in terms of four different types (Huang & Rust, 2018). The first type is mechanical intelligence, which is suited for the implementation of activities not involving the use of intellect by humans. These operations are 'boring' for people and can be translated into algorithms in a relatively simple way. The second type is analytical intelligence, which is about the human being's ability to gather information from the external world and process it in a well-defined context. This is a more complex level of AI, as the machine must be able to understand, interpret, and transform external information into data. The third and fourth types of AI defined by Huang and Rust (2018) are respectively intuitive intelligence and empathetic intelligence. In the former case, machines can develop and follow their intuition, such as a human mind, and generate immediate ideas without logical processes; then, their cognitive faculties subsequently develop and analyze these intuitions. With empathetic intelligence we move to the emotional sphere; this is the most complex form of AI as empathy is the ability to understand the emotions of others and respond to them appropriately by identifying their personality.

Prior research in industrial marketing reports AI is a critical technological infrastructure in several business activities and processes, such as pricing, management, buyer behavior (Martínez-López & Casillas, 2013), and sales (Syam & Sharma, 2018). AI offers B2B marketers the opportunity to convert data about customers, final users, and other business stakeholders into specific and heterogeneous types of market knowledge (Paschen et al., 2019). With specific reference to value co-creation, scholars paid great attention to the adoption and implementation of AI and robots by technology service providers in the last few years[1] but did not offer detailed analysis about how these machines can influence value co-creation (Kaartemo & Helkkula, 2018). This research domain, thus, is not only promising for the current lack of empirical research, but also for the undeniable suitability and affinity of the main characteristics and types of AI with the co-creation mechanisms adopted by providers and customers of industrial solutions to achieve an interactional creation of value.

2.3. Some industrial applications of AI-based solutions

In many industries, organizations are rethinking their strategies in order to take advantage of the digital revolution (Cantù et al., 2012; Gulati & Soni, 2015; Teece, 2018; Appio et al., 2020). Over the last few years, AI entered in several industrial domains such as logistics planning, stock market, robotics, law, scientific research, and even in the toy industry (Li, Hou, Yu, Lu, & Yang, 2017; Mele, Spena, & Peschiera, 2018). In retailing, by analyzing and processing data and information about the expense process of customers, AI informs engines for product recommendations and provides reliable suggestions for the physical location of items within a store (Grewal, Roggeveen, & Nordfält, 2017). AI is widely implemented also in the banking sector since a long time: its first inception dates back to 1987 when the Security Pacific National Bank (SPNB) in the USA organized a task force for the prevention of fraud related to the unauthorized use of credit cards (Christy, 1990). Since many years, AI is also used in the automotive industry (Gusikhin, Rychtyckyj, & Filev, 2007), in which autonomous vehicles can observe and analyze the speed and direction of other cars on the road and other third factors (e.g., traffic lights) and process all this information to carry out certain actions (e.g., change lanes, avoid obstacles).

Today, big data, digital technology, and AI are revolutionizing and creating new competitive landscapes also in the healthcare context (Wang & Hajli, 2017; Gastaldi, Appio, Corso, & Pistorio, 2018). In recent years, the World Health Organization and the International Telecommunication Union – two United Nations agencies – are establishing a focus group on Artificial Intelligence for Health (FG-AI4H) and developing a benchmarking process for health AI models that can act as an international, independent, standard evaluation framework (Wiegand et al., 2019). AI technologies in healthcare are used also to improve diagnostics and reduce human error (Meskó et al., 2018) as well as create value for different groups of stakeholders (e.g., patients, physicians, policymakers, payers) (Lehoux, Daudelin, Williams-Jones, Denis, & Longo, 2014). For instance, the recent pandemic outbreak of COVID-19 is calling entire governments to rethink their approach to healthcare, and they are doing it via AI. For instance, in China, the industrial colossus – Alibaba, Baidu, Huawei, Tencent – are all making available their AI-based solutions to solve the COVID-19 healthcare crisis. In their role of technology service providers, they are helping healthcare institutions and the central government to identify, track and forecast outbreaks; diagnose the virus; process healthcare claims; deliver medical supplies through drones; deploy robots that sterilize, deliver food and supplies; develop drugs and new vaccines; identify non-compliance or infected individuals; offer free online health consultations through chatbots.

3. Methodology

In order to answer the research question – how does AI enable and enhance value co-creation in industrial markets? – we use the case study methodology as an exploratory research tool (Eisenhardt, 1989) for investigating the case of Pieces Technologies. This pioneering firm in clinical AI[2] offers a very well documented example of a provider of AI-based solutions and, thus, represents a source of many reliable and varied secondary and primary data. Therefore, empirical richness (Weick, 2007) through a detailed narrative is valued upon. We focus upon an extreme case (Seawright & Gerring, 2008) in which the unfolding of events is sufficiently clear and contributes to enlighten how the AI-based solutions were conceived and implemented in value co-creation with healthcare organizations; with that, we were consistent with Pettigrew (1990, p. 275) when arguing that "if the phenomena to be observed have to be contained within a single or relatively small number of cases then choose cases where the progress is transparently observable." In line with Siggelkow (2007), we selected a powerful example, standing on unique descriptive and conceptual insights, involving multiple levels of analysis (individual, group, organization) (Yin, 2003). Overall, the use of single-case studies "can enable the creation of more complicated theories than multiple cases, because single-case researchers can fit their theory exactly to the many details of a particular case" (Eisenhardt & Graebner, 2007, p. 30). Through this qualitative research approach based on primary and secondary data, we use multiple sources of evidence for the triangulation of data (Yin, 2003).

3.1. Data collection and analysis

Data collection and analysis were organized in four phases: first, we relied on official and publicly available documents in order to collect information about the two software - *Pieces DS* and *Pieces IRIS*™ - which allowed us to better understand their functioning and characteristics. We also screened the different project outputs and articles with the aim to understand the outreach of those AI-based solutions. Second, we performed in-depth interviews (see Appendix 1) with key informants both at Pieces Technologies and from the B2B organizations in the healthcare ecosystem; they were instrumental to gain more insights about the 'what' and 'how' Pieces Technologies provided AI-based solutions, the impact of the AI-based solutions on the B2B organizations adopting them, as well as the relationship and value creation mechanisms between the technology service provider and B2B organizations. Third, 15 customers' reviews from hospitals, health systems, and community service organizations were also analyzed; they helped us, shedding further light on the motivations concerning the adoption of Pieces Technologies' AI-based solutions from the served B2B organizations, and the different value co-creation mechanisms enacted in the specific B2B healthcare context. Fourth, online documentation (i.e. reports, statistical data, trade press, and media publications) were collected and analyzed in order to check the overall magnitude of Pieces' AI-based solutions and their contributions to value co-creation in B2B.

Table 1 presents details of these sources and how they were used in

[1] 26 articles published between January 1996 and May 2018 (Source: Scopus).

[2] https://www.businesswire.com/news/home/20180305005158/en/Pieces-Technologies-NTT-DATA-Launch-Joint-Solution

Table 1
Data sources and use.

Source	Type of data	Use in the analysis
Official publicly available documents	*Pieces DS* and *Pieces IRIS*^{TM} software descriptions from official website Project outputs and articles published on the official blog page	Gather more software-specific information Understand the outreach and impact of Pieces Technologies' AI-based solutions
Interviews	*Spring 2019* 4 interviews: ● Mary Piepenbrink, RN, BSN, MBA, Executive Vice President, Sales and Customer Success, Pieces Technologies Inc. ● Andrew Masica MD, MSCI, Chief Clinical Effectiveness Officer, Baylor Scott & White Health ● Pete Perialis, Executive Vice President and Chief Strategy Officer, Children's Health ● Barron Lange, President, NTT DATA Services All interviews were audio-recorded and transcribed.	Gather data about the 'what' and 'how' Pieces Technologies provided AI-based solutions Gather information about the impact of the AI-based solutions on the B2B organizations adopting them Gather information about the relationship and value creation mechanisms between the technology service provider and B2B organizations
Data from the community	Users' reviews from hospitals, health systems, and community service organizations	Understand how the served B2B organizations adopted Pieces' AI-based solutions Unveil the value co-creation mechanisms in the specific B2B context
Other documents	Online reports, media publications, statistics, and trade press	Check for the magnitude of Pieces' AI-based solutions and their contributions to value co-creation in B2B

our data analysis.

3.2. Research setting

Founded in 2015, Pieces Technologies[3] is a US health and social information technology firm, based in Dallas, building software for analyzing and managing patient data in real-time. Pieces Technologies developed two main AI-based solutions. First, *Pieces DS* helps hospitals and health systems with the use of cloud data storage. The goal of this AI-based solution is twofold namely, identifying a health problem more quickly and efficiently, as well as providing immediate care in order to maximize the value co-creation between providers and customers. This technology envisages that the patient exposes the symptoms of the disease; then, information collected by the patient is compared with the databases in the cloud archive; afterward, the problem is identified, and the related care is quickly performed. All the information provided by patients over time is stored in the data archive to make the problem detection and its resolution increasingly efficient and precise. After the treatment is assigned, the patient is followed to monitor his health status and report any deviations from the results expected from the database.

The second AI-based solution is *Pieces IRIS*^{TM}, a data storage system that allows patients to be assisted outside the hospital. This technology links the healthcare organizations and the community services, offering a support program as well as social assistance in cases in which the disease can affect the emotional sphere of the patient. Indeed, the solution treats the patient holistically recognizing the fundamental importance of giving clinicians data and instruments to not only put in evidence medical treatment but also to help on patients' personal and emotional circumstances. Thus, *Pieces IRIS*^{TM} supports the patient in performing post-hospital care, improving life habits to avoid further health problems. Nowadays in the USA, around 25 hospitals use *Pieces DS,* and more than 100 community organizations and innovative health systems use *Pieces IRIS*^{TM} (see Table 2).

4. Findings

In this section, we detail the relationships between the four types of AI (Huang & Rust, 2018) used for the development of innovative services and the two key mechanisms of value co-creation in digital environments (Lenka et al., 2017). Our findings showcase how value co-creation can be achieved effectively if the technology service provider combines the most appropriate types of intelligence with the right mechanisms of interaction with its industrial partners.

4.1. Types of AI

Pieces Technologies develops B2B services for two market niches: (1) hospitals & healthcare systems and (2) social service organizations. Healthcare systems and stakeholders are repositories of a huge amount of collectible and codified knowledge which can potentially reduce the risk of medical errors and properly inform healthcare decision-makers. What Pieces does is to exploit knowledge within healthcare systems and hospitals via mainly (but not only) mechanical and analytical intelligence in order to offer its services to customers and improve the quality of care and the overall patient satisfaction. These B2B solutions use predictive analytics models/algorithms through which healthcare systems and organizations can turn critical points (e.g., excessive length of stay in hospitals) into opportunities for value creation. During the interview, the Executive Vice President of Sales and Customer Success at Pieces Technologies stressed how exploiting knowledge from healthcare stakeholders through AI-based predictive analytics models/algorithms was at the core of Pieces Technologies' developments even before its foundation:

> *"The Pieces journey started at Parkland Health & Hospital System in 2007, Dallas' large safety-net hospital system, when the founder, Ruben Amarasingham, MD, MBA, began developing predictive models to prevent readmissions. While many companies - large and small - claim the ability to deploy AI in real-time across health systems to surface key information, including social determinants of health, Pieces has deployed AI solutions over the past 2 years activating care team members within their clinical workflow."*
>
> Mary Piepenbrink, RN, BSN, MBA
> Executive Vice President, Sales and Customer Success
> Pieces Technologies

Care management is the main business within this market niche. An interesting example shows the contribution of Pieces Technologies in reducing patients' length of stay in hospitals through the deployment of a specific software-based on different types of AI - and modifying one simple aspect of the healthcare process namely, the module for readmission. In detail, intending to determine the risk of readmission and course of actions to adopt to decrease that risk, Pieces exploited both mechanical and analytical intelligence developing a solution that can analyze multiple variables in both structured and unstructured sources. The same goes for early warning systems/sepsis modules. The software

[3] https://piecestech.com

named *Pieces DS* analyzes multiple variables in structured and unstructured sources to determine the risk of impending inpatient deterioration and identify which organs should be treated to mitigate such a risk. As the CEO of Pieces Technologies recently put it[4]:

> *"Pieces Decision Sciences (DS) platform is a cloud-based software platform that improves the quality and cost of care by applying key algorithms at every step of a patient's care in real-time. The platform can be bi-directionally integrated with the electronic medical record (EMR) or other non-EMR systems and incorporates multiple data types, including structured, unstructured, and imaging data. The system interprets this data using a wide variety of algorithms to provide support for core decision-making tasks across a growing library of clinical and operational situations. Pieces Technologies has found that clinical, operational, and population health problems can be optimized by applying five categories of real-time algorithms. The algorithm categories can be broadly categorized as: Identification algorithms, Prediction algorithms, Activation algorithms, Monitoring algorithms, and Learning or Review algorithms. Pieces DS applies these algorithms at every stage of a patient's care."*
> Ruben Amarasingham, M.D, M.B.A
> CEO
> Pieces Technologies

By leveraging upon the combination of Pieces AI predictive models to monitor elevated risk patients, along with the capability of customers to implement systems devoted to integrating new data into the daily workflow, allows hospitals to improve outcomes and reduce risks. A recent interview[5] by Laurie Barenblat, M.S., Impact Consultant for Pieces Technologies clarifies more this point:

> *"A large regional health system reduced readmission rates by implementing Pieces DS, which uses AI to rapidly identify at-risk patients in the EMR. This hospital utilized Pieces' All-Cause Readmission Risk (ACRR) model to identify its target population of high and very high-risk patients. The hospital then used a Pieces algorithm running Natural Language Processing (NLP) and machine learning on clinical notes to identify and track the patients in those higher risk groups who had pre-discharge follow-up appointments. 37% of patients across both risk groups had pre-discharge follow-up appointments, and those patients showed 9% and 12% lower all-cause 30-day readmission rates, respectively, compared to patients with no indication of pre-discharge follow-up appointments. Combined, the two groups showed an 8% lower all-cause readmission rate. Moreover, very high-risk patients with pre-discharge follow-up appointments had 17% lower readmissions within seven days.*
> *The hospital also found benefit in using the Pieces algorithms to identify additional components that affect higher-risk patients, namely socioeconomic and environmental factors, or the social determinants of health (SDoH). Analysis showed that patients experiencing one or more SDoH had significantly higher 30-day readmission rates (37% high risk, 19% very high risk). In addition, among the patients who had pre-discharge follow-up appointments, there was a nearly 20% higher readmission rate for those experiencing at least one SDoH compared to those who were not."*
> Laurie Barenblat, M.S.
> Impact Consultant

In addition to the four types of AI, the firm uses also complex analyses run by clinical experts for its advanced analytics services. The joint effect of commercializing the most advanced machine-learning technologies and gaining experience from the field encourages hospitals to undertake actions envisaging long-lasting positive changes (e.g., create whole-person care plans to improve healthcare outcomes) on all the patient journey phases.

Other more sophisticated care management services for post-care delivery are implemented by using the intuitive and empathetic types of intelligence. For instance, the intuitive intelligence implemented by Pieces *IRIS*® can learn and adapt intuitively based on the understanding of the patients' journeys and their needs. These solutions can derive real-time information from patients' clinical and social practices with a two-fold advantage: first, hospitals can suggest ad-hoc recommendations to patients; second, they can still creatively think of arranging future social needs effectively. Furthermore, Pieces *IRIS*® has been created with a bigger scope in mind. The premises were that first, normally almost 80% of the healthcare outcomes are determined by factors other than clinical care (i.e., social, economic, environmental, and behavioral determinants[6]); second, and relatedly, medical care is estimated to account for only about 20% of the modifiable contributors to healthy outcomes for a population.[7] To date, only 1% of hospitals and social service organizations share digital information which translates into underutilized data and multiple disconnected patients' journeys. As a consequence, it could be desirable to create a platform to deploy proactive healthcare interventions and extend the patients' journey beyond the hospitals' walls, connecting hospitals with social service organizations like hospices, psychiatric centers, schools, to name a few, till embracing families and figuring out optimal diagnoses and treatments by incorporating the social determinants of health. Then, the long-term aim becomes developing specific therapeutic care paying attention to interpersonal and social characteristics. For instance, one way to take care of patients' emotions while facing a disease is to rely on empathetic intelligence. In that vein, Pieces Technologies contributes to the improvement of B2B services for social organizations through Pieces *IRIS*®. This scalable, cloud-based case management platform allows for inter-agency referrals in order to address the social needs of the most at-risk individuals in different communities via AI:

> *"For those entities within the network, information sharing becomes easier through a fully integrated AI platform. For those entities outside of the network, the incentives to share information become apparent once community benefits are realized."*
> Mary Piepenbrink, RN, BSN, MBA
> Executive Vice President, Sales and Customer Success
> Pieces Technologies

The healthcare organizations involved in this network are able to quickly connect patients with the community in order to assist their journey beyond the hospital walls. Thus, these platforms represent solutions useful for managing the patients' journey since they support hospitals and healthcare systems before, during, and after the care delivery.

Pieces DS and *Pieces Iris*® proved effective and recent funding will allow Pieces Technologies to scale up their implementation. In fact, Pieces Technologies announced that it has closed a $25.7 million Series B funding round led by healthcare investment firm Concord Health Partners[8]. Existing investors Children's Health of Dallas and OSF Healthcare System, based in Illinois, also participated in the round. The investment will accelerate the Pieces' national distribution of its clinical analytics engine, *Pieces DS*, and social determinants of health (SDoH) platform, *Pieces Iris*®.

The COVID-19 pandemics is further accelerating this process and recent technological developments are being implemented to face it.

[4] https://www.disruptordaily.com/ai-in-healthcare-use-case-pieces-technologies/
[5] https://www.disruptordaily.com/ai-in-healthcare-use-case-pieces-technologies/
[6] https://www.who.int/social_determinants/en/
[7] https://nam.edu/social-determinants-of-health-101-for-health-care-five-plus-five/
[8] https://www.dallasnews.com/business/health-care/2020/01/07/dallas-startup-raises-257-million-to-launch-hospital-readmission-reducing-software-nationwide/

Table 2
The connected healthcare community with Pieces Tech.

Type of organization	Names	Link
Health system	Baylor Scott & White Health	https://www.bswhealth.com/
Social organization	The Metro Dallas Homeless Alliance (MDHA)	https://mdhadallas.org/
Social organization	The Y	https://www.ymca.net/
Social organization	The Salvation army	https://www.salvationarmy.org/
Social organization	Dallas County Community College District	https://www.dcccd.edu/pages/default.aspx
Health system	Maricopa Integrated Health System	https://mihs.org/
Social organization	Unlocking Doors	https://www.unlockingdoors.org/index.html
Health system	Northwell Health	https://www.northwell.edu/
Hospital	Parkland	https://www.parklandhospital.com/
Hospital	Washington Hospital Healthcare System	https://www.whhs.com/
Care Coordination Software	Ensocare	https://www.ensocare.com/
Global IT Innovator	NTT Data	https://www.nttdata.com/global/en/
Social organization	Children's Health	https://www.childrens.com/
Social organization	Sharing Life Outreach	http://www.sharinglifeoutreach.org/home.htm
Hospital	Parkview Medical Center	https://www.parkviewmc.com/
Social organization	North Texas Food Bank	https://www.ntfb.org/
Global Consultancy	Huron	https://www.huronconsultinggroup.com/
Social organization	PCCI	https://pccinnovation.org/
Health System	OSF Healthcare	https://www.osfhealthcare.org/

Indeed, Pieces Technologies announced the development of a COVID-19 module that will aid health systems' response to the novel coronavirus. Using Pieces DS, a specifically configured COVID-19 module will track potentially at-risk patients, pre and post-testing; monitor patients for clinical deterioration directly in a hospital's electronic medical record; and support resource planning and risk stratification for health system administrators[9]. Intensive care unit (ICU) triage decisions, outcomes management, and capacity planning for hospitals is becoming a critical issue with the influx of patients with COVID-19 symptoms. Pieces' software looks at all data points, including labs, doctor's notes, and screenings, in real-time, to create a comprehensive COVID-19 registry[10]:

> *"We work with major health systems across the United States, and it became quite clear early on that our machine learning and AI capabilities, together with our software, would provide priceless value under these conditions."*
> "Our data science teams moved quickly to optimize and deploy our software to support health systems on the front-lines battling this epidemic."
> Fayiaz Chaudhri
> President
> Pieces Technologies

4.2. Value co-creation

This subsection provides an overview of the key mechanisms of value co-creation implemented by Pieces Technologies. All the informants and evidence found in secondary sources demonstrate the role of Pieces Technologies in designing solutions with the aim to promote value co-creation with its customers (i.e. hospitals, healthcare systems, and social service organizations). Strong evidence of such corporate orientation for co-creation emerges from the R&D approach of the firm:

> *"Pieces Technologies adheres to rigorous protocols to develop the most robust and reliable models with demonstrated benefit for our partners. Analysts and clinicians work together to develop, implement, and monitor models incrementally through multiple cycles of model development, implementation, evaluation, redevelopment, and more."*
> Mary Piepenbrink, RN, BSN, MBA
> Executive Vice President, Sales and Customer Success
> Pieces Technologies

The same informant explains that a customer-centric approach, which is usually adopted during the early stages of the implementation of new technological solutions, in this case, it is also used during the implementation of the AI solution within the customer organization:

> *"After implementation, Pieces employs 'sustained' efforts that include not only typical support, account management, and governance, but also Pieces physician-scientists and data scientists, to further assist customers in deeper data analysis to identify ongoing opportunities and process improvements that can be used as best practices across the enterprise."*
> Mary Piepenbrink, RN, BSN, MBA
> Executive Vice President, Sales and Customer Success
> Pieces Technologies

More in detail, our empirical evidence points out Pieces Technologies implements both responsive and perceptive mechanisms of co-creation in order to satisfy the needs of a heterogeneous set of actors of any healthcare system (e.g., physicians, analysts, patients, policy-makers, and customers). The same logic applies, as illustrated in the remainder of this subsection, for the selection and establishment of external partnerships. Healthcare professionals and firms are the preferred type of customers for value co-creation. Indeed, all the informants stress that Pieces Technologies is used to exploit clinical knowledge held by clinicians and healthcare organizations, to initially segment a clinical problem of potential value, and identify outcomes and potential predictors of interest.

As reported above, perceptive mechanisms of co-creation aim at improving the effectiveness and efficiency, customer-centricity of the offer, and the optimization of operations. This mechanism is the most used by Pieces and has played a fundamental role in shaping the partnership with Parkland Hospital in Dallas. The partner created an information-sharing network providing healthcare to the most vulnerable groups of citizens of the community before they could come to the emergency room.[11] This network employs mechanical and analytical intelligence to reduce unnecessary hospitalizations, generate economic savings, and improve the quality of life for these social categories. A further implementation of perceptive mechanisms is the partnership between Pieces Technologies and Metrocare Services, the largest

[9] https://www.businesswire.com/news/home/20200327005045/en/Identify-Predict-Track-Patients-Risk-COVID-19
[10] https://www.businesswire.com/news/home/20200327005045/en/Identify-Predict-Track-Patients-Risk-COVID-19
[11] https://www.politico.com/magazine/story/2017/12/18/parkland-dallas-frequent-flier-hospital-what-works-216108 (accessed on 16–09-19).

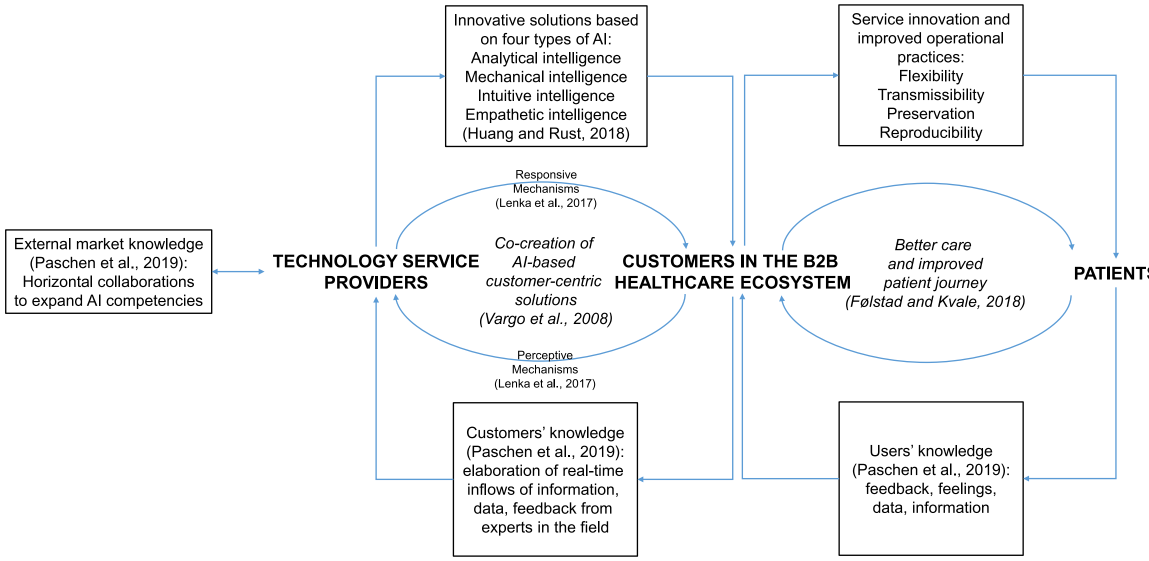

Fig. 1. Integrative framework connecting value co-creation and improved patient journey.

provider of mental health services in North Texas. Via this collaboration, based on both analytical and mechanical intelligence, firms aim to provide a more thoughtful, comprehensive whole-person care by bringing together unique predictive analytics and behavioral health.[12]

In some cases, both mechanisms (perceptive and responsive) and intuitive and empathetic intelligence can be used for co-creation. For example, in 2016 the firm established a commercial collaboration with Baylor Scott & White Health (BSWH), a US group of private hospitals, in order to identify indicators of quality, safety, and patient experience, in addition to providing advanced analytics systems based on intuitive and empathetic types of AI. In this way, hospitals can achieve both a more customer-centric offer and a more flexible revenue model. This twofold ambition is remarked in the following statement:

> *"What struck us at BSWH was the comprehensive nature of the Pieces platform, particularly the ability to match individual patient needs with organizational and community."*
> Andrew Masica, MD, MSCI
> Chief Clinical Effectiveness Officer
> Baylor Scott & White Health

This example shows that the technological platform and the cloud service of data storage are the core elements by which the provider and customer of the B2B services can co-create value via both the responsive and perceptive mechanisms and four different types of AI. Thus, the entire service ecosystem can benefit from the co-created value on these platforms, providing a solution for comprehensive case management. Healthcare organizations are supported by precision tools that are able to ensure a high level of the right care to the right patients at the right moment. Hospital services are improved in terms of cost and time savings, reduced search costs, expanded range of services, minimized readmissions, and reduced length of stay. All these benefits contribute to improving the patient journey before and after the care, providing ongoing collaboration among physicians and social organizations to ensure patients remain connected in the community and stay healthy. Thus, the same hybrid approach is also used for providing B2B services to social service organizations. This emerges from the information reported about the commercial relationship with Children's Health, which will utilize *Pieces DS* for implementing predictive modeling (a responsive mechanism) supporting streamline clinician workflows and improving patient outcomes (a perceptive mechanism):[13]

> *"As a system, Children's Health is committed to providing care and promoting healthier living in the community. Through the Pieces Technologies platforms, we are able to improve health outcomes by processing and integrating patient data and initiating earlier interventions in children."*
> Pete Perialis
> Executive Vice President and Chief Strategy Officer
> Children's Health

Recently the firm established horizontal collaborations, aimed at initialing both responsive and perceptive mechanisms of co-creation with future customers via the exploitation of mechanical and analytical intelligence. On one hand, in January 2018 Pieces Technologies began a collaboration with NTT Data Services to expand its AI competencies. As reported on the official corporate blog:[14]

> *"We are committed to delivering practical, innovative solutions that solve our clients' daily challenges…This collaboration with Pieces Technologies will deliver true clinical value and drive sustainable change for our healthcare clients moving to value-based care models."*
> Barron Lange
> President
> NTT DATA Services

On the other hand, a case of horizontal collaboration enabling both perceptive and responsive mechanisms of co-creation with future customers is the 2019 technological collaboration with Ensocare, a US firm realizing software for service-enabled care coordination. Via this partnership, the two software firms release an AI solution combining hospital discharge software with an application that links patients with community services; the partnership between the two firms aims to reduce readmissions and improve care outcomes.[15]

Finally, the use of different types of AI through perceptive and

[12] https://www.businesswire.com/news/home/20160913006012/en/ADDING-MULTIMEDIA-Metrocare-Services-Pieces-Technologies-Partner (accessed on 16–09-19).

[13] https://www.businesswire.com/news/home/20180712005169/en/Pieces-Technologies-Continues-Collaboration-Children%E2%80%99s-Health

[14] https://piecestech.com/media-pub/ntt-partnership

[15] https://piecestech.com/pieces-tech-ensocare-join-forces-address-patients-social-determinants-health/

responsive mechanisms improve service and operational practices for the value co-creation in B2B markets in terms of *flexibility* (e.g., files can be saved in various formats beyond the classic PDF); furthermore, it is possible to accompany it with different documents such as audio and images; *transmissibility*, because thanks to the use of AI-based solutions the information can be transmitted anywhere and anytime; *preservation*, the files can be kept indefinitely, reducing the difficulty of space and management of classic paper archives, including deterioration. The consultation time and difficulties of the previous system can be dramatically reduced, facilitating and speeding up the access to the documents; *reproducibility*, in that infinite copies of the document can be produced.

5. Discussion

Our results show that technology service providers and customers in the B2B healthcare ecosystem (i.e. hospitals, healthcare systems, social service organizations) can generate high-quality service innovation (novel industrial solutions) only by leveraging upon different types of AI (Huang & Rust, 2018), virtuous value co-creation dynamics through specific mechanisms (Lenka et al., 2017), and taking stock of the contributions of the different types of market knowledge (i.e. customer knowledge, user knowledge, and external market knowledge) (Paschen et al., 2019).

We derive an integrative framework (see Fig. 1) that shows how technological providers and customers operating in a B2B ecosystem can enable and enhance the co-creation of AI-based customer-centric solutions (Vargo, Maglio, & Akaka, 2008) and the extent to which this can generate better care and an improved patient journey (Følstad & Kvale, 2018). An iterative loop is enacted between the technology service provider and the customers through the implementation of perceptive and responsive mechanisms (Lenka et al., 2007). The co-created AI-based solutions revolve around different types of intelligence – analytical, mechanical, intuitive, and empathetic (Huang & Rust, 2018) – as well as internal and external knowledge streams stemming from customers', final users, and horizontal collaborations (Paschen et al., 2019). Real-time elaborations of customers' information, data, and feedback from the field are vital for improving the iterative loop based on perceptive and iterative mechanisms. The iterative loop is necessary but not sufficient for the technology service provider in that external market knowledge is instrumental to broaden its AI competencies and improve the effectiveness and innovativeness of the provided solutions. The integrative framework also highlights the type of performance improvements customers get at the level of service and operational practices (in terms of flexibility, transmissibility, preservation, reproducibility) once an increasing quantity and quality of users' knowledge inflows from patients. Feedback, feelings, data, and information become a critical asset for aptly implementing the second iterative loop, resulting in better care and an improved patient journey.

Overall, the AI-based service providers promote value co-creation by deploying rigorous protocols, reliable models, and a customer-centric approach. Perceptive and responsive mechanisms of value co-creation are enacted together in the most complex cases, usually related to the accomplishment of better customer-centric offers and more flexible revenue models (see commercial collaboration with Baylor Scott & White Health focused on advanced analytics systems based on the application of mechanical, analytical, intuitive, and empathetic intelligence), or the need to streamline clinician workflows and improving the overall patient outcomes (see commercial collaboration with Children's Health). Interestingly, the technology service provider adopts a strategy of horizontal collaborations with other providers in order to improve its AI competencies and provide increasingly sophisticated AI-based solutions (see collaboration with NTT Data Services and Ensocare). This is in line with the importance Paschen et al. (2019) give to external market knowledge as a means to enhance technology service providers' offers.

Our findings contribute to two different streams of knowledge. First, we contribute to the theory about value co-creation via AI in industrial markets (Martínez-López & Casillas, 2013; Marcos-Cuevas et al., 2016; Paschen et al., 2019) by providing a holistic view and integrative framework of how value co-creation can be enabled and enhanced. As reported before, our analysis integrates the characteristics of the different types of AI (Huang & Rust, 2018) with the value co-creation mechanisms (Lenka et al., 2017) and different types of market knowledge (Paschen et al., 2019). Formerly disconnected, these three aspects offer a clearer and more structured view on how to generate high-quality service innovation and achieve value co-creation (Vargo et al., 2008). Digital platforms and other co-created assets (Ehret & Wirtz, 2018) are not likely to generate value and innovation if the combination of such elements is poorly designed.

Second, our study contributes to the literature about AI in services (Kaartemo & Helkkula, 2018; Huang & Rust, 2018) by offering a multidimensional snapshot of the most relevant dimensions and options that providers of AI-based industrial solutions should consider in order to implement service innovation. For instance, this study highlights different ways to improve service and operational practices at the level of transmissibility of information, flexibility and preservation of files, reproducibility of documents), emerging thanks to the use of AI-based solutions which guide and improve the patient journey within the B2B healthcare ecosystem.

Only relying upon the four different types of AI would not be a sufficient condition to create value for industrial partners (or even final users, i.e. patients). What makes the difference is the integration of the AI types with the value co-creation mechanisms (perceptive and responsive) and the different types of market knowledge, for a great part of data, information, and feedback come from interactions with human beings who, in turn, express their feelings and expectations in complex ways. The inter-organizational relationships are iterative in nature, and even the most complex needs and feelings find a way to be captured and translated by the proposed AI-based solutions. In this sense, conceiving an effective service innovation in the digital transformation era has at its foundations an effective human–machine interface nurtured by a continuous exchange of knowledge (Razmerita, Phillips-Wren, & Jain, 2016; Paschen et al., 2019).

6. Implications for theory and practice

Drawing on the above-reported findings and integrative framework, some policy and implications can be advanced.

An interesting implication for scholars of AI-driven value co-creation in B2B ecosystems is that the proper management and exploitation of such technologies cannot occur without paying attention to the issues of management and acquisition of data, information, and distillation of relevant knowledge. As a consequence, value co-creation in such business contexts is inevitably related to knowledge management theory. A second interesting implication is that services derived from effective AI-based solutions have to generate positive outcomes for not only providers and customers; in fact, final users and other stakeholders should gain benefits from the value co-creation dynamics. For these reasons, within a business context driven by AI-based solutions, the provider can support the exchange of data and information via broader and hybrid (perceptive and responsive) mechanisms of value co-creation (Lenka et al., 2017). The use of different types of AI (mechanical, analytical, intuitive, and empathetic) (Huang & Rust, 2018) could greatly vary across different users in B2B markets since their intention to benefit could be disparate. It depends on the different goals in each industry. Thus, the recipient of AI-based solutions (the customer) must be completely engaged in the process (Marcos-Cuevas et al., 2016) and has to widely and continuously support the functioning of these mechanisms of co-creation. Thus, researchers in this field should take into account that only the adoption of a community-level perspective can provide a comprehensive overview of the dynamics of such business and technological phenomena. Finally, evidence suggests that more types of intelligence and co-creation mechanisms have to be integrated in order to develop valid AI-based solutions which, in turn, emphasizes the idea that only sophisticated analyses can provide effective marketing strategies for AI-based solutions in B2B ecosystems oriented to services.

The results of the present study also stress some interesting managerial and marketing implications for industrial firms willing to implement the digital transformation by adopting AI-based solutions. First, these organizations need to carefully understand what is the most suitable combinations of intelligence, mechanisms, and knowledge sources to market and deliver successful AI-based solutions in B2B ecosystems oriented to services. These combinations, of course, should be chosen also with the constructive support and collaboration of customers. Such requirements highlight the need for industrial firms to reinforce effective and continuous information exchanges with the main customers of their services. Second, firms should also take into account the issue of technological complexity when they co-create and design their AI-based solutions. Since the various types of AI are related to different levels of complexity, managers should implement a preliminary cost-benefit evaluation of each solution. For instance, if expected profits are not relevant in the short-medium term, then it would be advisable to exploit just mechanical or analytical intelligence and enact a perceptive mechanism of co-creation. Intuitive and Empathetic models are useful when firms establish a long-term relationship with their customers, providing creative problem-solving through a responsive mechanism of co-creation.

Finally, the results of our study outline two relevant policy implications. First, policymakers willing to boost the adoption and implementation of AI-based solutions within an industrial market should pay great attention to what are the most (and least) suitable types of AI for that particular business context. For instance, the dramatic circumstances caused by the COVID-19 pandemic, enforce severe reflections on the structure of the healthcare ecosystems. The investigation of the systemic criticalities that emerged in the management of COVID-19 lead to the observation that the effectiveness of the measures to contrast it is closely connected to the ability of the territorial health to respond to the emergency. AI-based solutions can be useful to plan a new clinical and managerial governance of healthcare ecosystems and fight the lack of access to diagnoses and fast treatments by cross-referencing data provided by different sources. Second, public agencies promoting AI-based services should push industrial players to involve final users in their R&D projects. Indeed, the more final users are involved in such projects – by providing real-time feedback and information –, the more industrial players can better understand what are the criticalities faced by their customers serving the final users, therefore designing and co-creating better B2B services via improved perceptive and/or responsive mechanisms.

7. Limitations and future research

The limitations of the present study are twofold. First, single case study research is a leading research method offering relevant insights and evidence in business studies. However, various problems, such as complexity and network boundaries, might undermine the value of case study research when this method is implemented for investigating B2B markets (Halinen & Törnroos, 2005). Such problems are exacerbated by the potential of AI which, by definition, can provide highly specialized, sophisticated, and context-specific solutions. The issue of generalizability more evidently emerges in the second limitation of the study, which reports on a case from healthcare. This is an industry where value co-creation is a well-known and critical goal for all the industrial actors (e.g., public institutions, private firms, hospitals, etc.) from any healthcare system (Schiavone & Simoni, 2019). However, in other sectors in which the co-creation dynamics and mechanisms are less common or less affected by value-based paradigms, the implementation of AI-based solutions might follow different application paths and logic. Finally, scholars might explore via longitudinal studies if (and to what extent) the adoption and implementation of AI-based solutions by an existing business network, within which former digital technologies are already in use, change the nature of business relationships among its industrial partners and their preferences in terms of co-creation mechanisms.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix 1. Semi-structured interview

Section 1 – Firm profile

1.1: Briefly describe how your firm was founded.

1.2: Illustrate the organisational units of your firm.

1.3: Describe the main trends in AI industry in 2020 and the current market positioning of your firm within it.

Section 2 – Business model

2.1: Can you describe the following 9 "building blocks" of the business model of your firm?

1. key partners:
2. key resources:
3. key activities:
4. value proposition:
5. customer segments:
6. customer relationships:
7. channels:
8. cost structure:
9. revenue streams:

2.2: Among these 9 building blocks, which is/are today the most important for achieving a sustainable competitive advantage in your firm sector?

2.3: Describe, if any, the main changes (and their causes) to your business model occurred over the last 5 years.

Section 3 – Technologies, services, and products

3.1: Briefly describe the technology/product/service portfolio of your firm. What are your core products and the latest innovations?

3.2: Describe your target-segments and main customers of your core products. If available, provide some data.

3.3: Illustrate the typical process of new product/service development implemented in your firm. Do you usually involve your customers, suppliers, and/or external partners?

[16] Earlier versions of this article were presented at the EIASM Conference "Joint Paper Development Workshop - Internationalization, Entrepreneurship and Innovation. A multilevel perspective", organized by the Universities of Napoli Federico II, Bergamo, and Pavia (13–14 June 2019, Napoli, Italy) and at the Paris School of Business (France) during a research seminar (22 October 2019, Paris, France).

Section 4 – Patient journey

4.1: List and comment on the main criticalities and issues for patient journey managed and performed without and/or before adopting AI. If possible, cite and provide information about real cases.

4.2: Describe how the patient journey delivered by your customers changed after the application of your AI-based services.

4.3: Which are the benefits in terms of mapping of patient journey achieved by your customers via AI? Are there any specific techniques or models to use for the mapping of the patient journey?

4.4: Explain how your customers should revise their internal organisation, business model, and strategy in order to adopt and implement successfully AI-based services? Any managerial suggestions and/or risks to avoid?

4.5: How do your customers create value and increase profits via their novel AI-based patient journey? If possible, cite and provide information about real cases.

4.6: To what extent AI enacts you to co-create with your customers? Please, provide some examples.

Section 5 – Industrial marketing

5.1: Describe the impact of your AI-based services on the business context and business relationships of healthcare firms (your customers and not only them). Please provide also, if available, some data and empirical evidence.

5.2: How does AI affect the set of relationships inside the healthcare ecosystem? Does AI generate new networks of health firms and/or providers?

5.3: How do real-world data and information used for AI can improve health care policies, access to care, and health technology assessment?

5.4: How do you contribute to optimize the customer journey through AI?

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