Integration of knowledge and technology in the co-production of AI-based solutions for the healthcare sector

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Abstract

Purpose – This article aims to explain how organizations create and integrate medical knowledge to develop AI-based medical solutions. The study resulted from a discussion on value co-production with digital technologies and the capabilities needed for it.

Design/methodology/approach – The study explores the case of value co-production with the digitalization of traditional medical stethoscopes. It considers integrated resources to create AI-based medical solutions, actors engaged in co-production and activities related mainly to knowledge embodiment.

Findings – This article presents operand and operant resources integration when AI is implemented in innovative medical solutions. Furthermore, it shows which activities are undertaken for value co-production and what roles actors from various fields play in resource integration.

Originality/value – Our article discusses the integration of knowledge and the role of knowledge embodiment among resource integration in value co-production when working on AI.

Keywords AI-based value, Value co-production, Healthcare, Resource integration, Knowledge embodiment

Paper type Research paper

Introduction

Technologies such as artificial intelligence (AI) can provide reliable support in determining the medical diagnosis and the best course of treatment (Gómez-González *et al.*, 2020). Artificial intelligence can collect data about the environment and exercise action to achieve its goals (Russell & Norvig, 2009). Medical AI-based solutions combine diagnostic data and medical

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knowledge with the excessive analytical potential of advanced technologies. The applications of AI in medicine have grown considerably and are now under development in nearly every medical specialty (Hadley, Pettit, Malik, Khoei, & Salihu, 2020). Moreover, AI can deliver value by providing a diagnosis, determining the best treatment course (Shah & Chircu, 2018), and shifting healthcare from the hospital to domestic care (Lam, Ho, Mo, & Tang, 2021). Researchers suggest that AI can perform as well as or better than humans at diagnostic healthcare tasks (Davenport & Kalakota, 2019).

Interdisciplinary knowledge is required to provide value for users of complex digital systems. Therefore, several authors emphasize the importance of collaboration between various actors in developing such systems (Alahmari *et al.*, 2022). Researchers present the value of the co-creation process when digital technologies are implemented. However, no researcher has conducted a fully equivalent study to understand how organizations cooperate with the support of AI when knowledge is the critical resource needed for value. Studies scarcely explain how value co-creation is linked to its outcomes when AI is applied. In the medical context, recent studies consider the value of co-production through digital technologies from the patients' and providers' perspectives (Balta, Valsecchi, Papadopoulos, & Bourne, 2021). However, they scarcely explore it in an organizational setting context (Kaartemo & Känsäkoski, 2018). There is a need for a better understanding of how organizations can integrate medical knowledge thanks to the development of algorithms for better recognition of diseases.

We aim to explain how organizations create and integrate medical knowledge to develop AI-based medical solutions. Value creation between organizations is complex and multidimensional, meaning we could not approach it as a one-sided, provider-focused process. Thus, we embed our study in an interactive understanding of business (service-dominant logic, interactive/network approach). Specifically, we approach value creation with the concepts of value co-production (Ramirez, 1999) and knowledge management theory (Ferreira, Mueller, & Papa, 2020). This motivated our research questions (RQ1): How is value co-production interpreted in the context of AI-based solutions? (RQ2): What resources are integrated into AI solutions? (RQ3): How are resources integrated when AI solutions are co-produced? RQ4: Who combines resources in the co-production of AI solutions?

To answer those questions, we applied an explorative method. We aimed to learn from the case pertaining to the digitalization of traditional medical stethoscopes transformed into AI-based tools for diagnosing lung disease combined with a mobile app that assists doctors and patients with a solution. Thus, we addressed the development of diagnostic medical solutions that collect data on patient health, analyze it using AI algorithms, and provide diagnoses for a doctor and recommendations for the patient (Gómez-González *et al.*, 2020). However, we did not analyze how patients and doctors use this medical solution as other scholars have studied it (Gaczek, Leszczyński, & Zieliński, 2022; Grzywalski, Szajek, *et al.*, 2019).

Our article contributes to the literature on value co-production by addressing its two streams, namely service-dominant logic and interactive/network approach. First, the study enriches the discussion on integrating operand (the objects of operations) and operant resources (used to make operations) in value co-production (Paschen, Kietzmann, & Kietzmann, 2019) by highlighting the role of knowledge embodiment (transformation of knowledge into a form in which its value becomes evident) when working on AI-based solutions. Second, the study emphasizes the roles played and activities taken by actors of interdisciplinary knowledge when working on AI technology (e.g. Adadi & Berrada, 2018). This article also adds to an increasing stream of studies in healthcare on the role of technology-enabled capabilities from the point of view of delivering medical services through technology (Balta *et al.*, 2021). From a managerial perspective, our article suggests practical recommendations for managers working on AI-based solutions to transform knowledge into a medical system with AI. It offers pathways and activities for the co-production of AI-based medical solutions related to integrating resources, engaging interdisciplinary teams, developing medical solutions, certification, and regulatory processes.

The present work is structured as follows. First, we will provide an overview of the critical concepts involving AI-activated value, resource integration, and knowledge embodiment. Then, we will justify the research method and present the findings. Lastly, we will discuss the results of their contribution and suggest practical implications.

Literature review

Co-production as a means of value co-creation

Researchers recognize that value for professional customers derives from the use of a product rather than from the quality of manufacture or the value determined during an exchange transaction (Eggert, Kleinaltenkamp, & Kashyap, 2019). Usually, value-in-use is viewed as the outcome of a collaborative process in which actors collaborate to co-create value (Friend, Malshe, & Fisher, 2020). It involves joint actions of business actors, in which each partner brings unique resources, capabilities, and expertise to create a solution to customers' needs. Value co-creation rests on the principle that businesses can achieve tremendous success by working together rather than alone.

Value co-creation literature attempts to provide an array of related concepts regarding different stages of collaboration (e.g. co-innovation, co-design, and co-production). Value co-production focuses on integrating actors' resources by a provider in a collaborative process (Massi, Rod, & Corsaro, 2020). It differs from co-creation in two ways. First, co-production focuses on creating value for customers, while co-creation focuses on experiencing it with the customer. Second, the responsibility share differs – in the case of co-production, the provider takes responsibility for value creation; in the case of co-creation, actors take it jointly (Saha, Goyal, & Jebarajakirthy, 2022).

Researchers agree that value co-production occurs as an outcome of resource integration (Lenka, Parida, & Wincent, 2017). Taking the Service-Dominant Logic approach, Vargo and Lusch (2008) suggest that resource integration should be considered from the perspective of operand resources, objects, and operant resources used on operand ones to produce effects. That stream of research considers integrating the resources and capabilities of two or more businesses (Prenkert *et al.*, 2022). Researchers study operant resources to understand how sharing knowledge, skills, and expertise contributes to developing new products, services, or processes that meet customers' needs (Bonamigo & Frech, 2021). An interactive/network approach serves to understand which professional actors act together and how they integrate resources (Baraldi, Gressetvold, & Harrison, 2012). These studies focus on interfaces implemented by actors for resource integration. They explore the types of actors involved in resource integration and their activities in co-producing a solution around a patient's needs by incorporating complex resources of collaborating actors in the healthcare ecosystem (Russo-Spena, Mele, & Marzullo, 2019).

Value co-production continues advancing toward increased digitalization. Digital technologies enable and enhance resource integration by managing a comprehensive set of multi-level interactions entailing several industry stakeholders (Ramaswamy & Ozcan, 2018; Leone, Schiavone, Appio, & Chiao, 2020; Paschen, Kietzmann, & Kietzmann, 2020). Artificial intelligence activates value that stems from collaborating on data analytics and the application of machine learning (Kot & Leszczyński, 2022). However, operating on data requires actors to possess skills and capabilities related to data literacy for identification, understanding, and reacting to digital needs (Lenka *et al.*, 2017; Struwe & Slepniov, 2023).

AI-based value co-production in the healthcare context

Healthcare organizations have transitioned from a volume-oriented to a value-oriented approach and managers are paying more attention to performance and adding value (Laurenza, Quintano, Schiavone, & Vrontis, 2018). The value of the healthcare system depends on providing effective care to those in need and builds on three key pillars: (1) addressing patient preferences, (2) precisely matching the patient's profile with the treatment, and (3) providing access to physicians and monitoring services that maximize satisfaction and minimize burdens (Agarwal, Dugas, Gao, & Kannan, 2020). Thanks to the high power of data processing and analysis, AI allows for a breakthrough in value creation and delivery in healthcare in the context of all three value dimensions (Choi *et al.*, 2016). Thus, in the healthcare context, AI-based value displays complexity and multidimensionality (Table 1). Hence, we should consider it on the levels of the healthcare ecosystem: individuals (e.g. support for decision-making and health monitoring), organizations (workflow management, performance improvement, cost reduction, and fraud detection), and sector (time-saving, lower resource consumption, better professional training, data sharing, and data availability) (Ali *et al.*, 2023). Feedback data collected from medical equipment users online and then analyzed by algorithms can generate data-network-effect added value: an excellent match to customer needs and increased productivity (Latinovic & Chatterjee, 2024).

The latest research on value in business studies in healthcare indicates the importance of producing value together by different actors. Service-dominant logic assumes value as generated between patients and service providers (Maglio & Spoher, 2008). Service science positions patients as skilled subjects who gather and analyze information about their health and self-manage their self-care, which creates value (Osei-Frimpong, Wilson, & Lemke, 2018). The industrial network approach considers actors in the health ecosystems as collaborators working together for value creation (Kokshagina & Keränen, 2022). Studies on digitalization highlight digital technologies as enablers of value creation in complex industries like healthcare (Balta *et al.*, 2021). Kulkov (2023) suggests that to create AI-based value in healthcare, scholars must analyze health records and data related to the procedures of physicians, scientific medical articles, and medical devices in order to train algorithms that identify patterns in such datasets. Such an approach may prove efficient in oncology and cardiology, where diseases are widespread, and recognition of symptoms remains essential for treatments.

Although value co-creation in the healthcare context is increasingly gaining scientific interest (Fusco, Marsilio, & Guglielmetti, 2023), there remains little literature investigating the effective integration of resources from different settings in the healthcare system when digital technologies are applied (Kaartemo & Känsäkoski, 2018). Moreover, scholars still do not understand how actors link their resources, what interfaces enable them, and how intangible resources like knowledge are integrated to create value. Furthermore, studies have not focused

Table 1. AI-based value in the healthcare context

Dimensions of value	Source
1. Customer diagnosis 2. Customer's response to interaction with the device and application	Rong *et al.* (2020)
1. Patients can proceed with diagnosis using technologically advanced equipment, get access to data, and obtain AI-based medical recommendations 2. AI technology enables new ways of medical service delivery	Balta *et al.* (2021)
1. Controlling users' health 2. Recommending evidence-based prevention decisions 3. Empowerment of patients	Samuel *et al.* (2022)
1. Diagnosis is based on an algorithm that analyzes data and delivers some recommendations 2. A virtual assistant that imitates a doctor or physician and communicates the result of the diagnosis to the patient	Gaczek *et al.* (2022)
1. Improved access to healthcare 2. Responsiveness 3. Privacy	Kulkov (2023)
1. Product value 2. Data-network-effect added value	Latinovic and Chatterjee (2024)

Source(s): Authors' own elaboration

on resource integration when AI is applied for value co-production in healthcare. Research on digital transformation in healthcare focuses mainly on internal changes in traditional institutions, technologies, health records, or health sector components. Still, it does not consider the inter-organizational perspective (Hermes, Riasanow, Clemons, Böhm, & Krcmar, 2020) and rarely links co-production with the value generated in healthcare (Fusco *et al.*, 2023).

Knowledge embodiment in value co-production in healthcare

Knowledge is a strategic resource for value co-production (Bonamigo & Frech, 2021). By applying it to operand resources, companies can create, transfer, and use their assets (Carayannis, Ferreira, & Fernandes, 2021). Knowledge emerges from data through interactions between implicit and explicit knowledge (Nonaka, Toyama, & Nagata, 2000). People can easily communicate, process, transmit, and store explicit knowledge. Meanwhile, gaining tacit knowledge requires sharing experiences, observation, and imitation (Hall & Andriani, 2002). Knowledge Management Theory acknowledges the value of tacit knowledge and emphasizes the need to make it explicit and sharable, even if it is difficult to articulate or document (Tzortzaki & Mihiotis, 2014). Knowledge management theory suggests organizations can capture and transfer tacit knowledge by documenting best practices, creating repositories, and promoting knowledge sharing. Leone *et al.* (2020) showed that it is possible in hospitals to use AI thanks to appropriate knowledge management. They highlighted the importance of integrating market knowledge, patient data, and AI solutions to create AI-based customer-centric organizational solutions for healthcare institutions.

In the case of health services, Knowledge Management Theory assumes that we should treat medical personnel as experts with exceptional knowledge resulting from their accumulated experience, their understanding and interpretation of phenomena and research in a specific health environment, and the synthesis of research results in a particular health environment (Wu & Hu, 2012). Doane and Varcoe (2008) illustrate how the ontological process plays a role in effectively integrating and translating nurses' medical knowledge into practice. In such translation, we may treat tacit knowledge as an operant resource – capable of creating value – that acts upon information (explicit knowledge) as an operand resource, i.e. one that requires some action to make it valuable (Wieland, Polese, Vargo, & Lusch, 2012). Co-production occurs at the junction of expert and patient roles in healthcare ecosystems if appropriate mediation is provided (Campbell, 2021) and actors have evidence-based knowledge and teamwork competencies (Yeung, Scodras, Salbach, Kothari, & Graham, 2021).

While research or diagnostic processes are codified to be easily translated into machine language, doctors rely primarily on their own experience in the diagnosis. In the case of AI-based medical systems, the critical issue remains the embodiment of knowledge, the transformation of knowledge into a form in which its value becomes evident (Demarest, 1997). Individuals create and transfer knowledge through their sensory experiences and physical interactions. Using tacit knowledge in value co-production requires integration with explicit knowledge through operant resources and interfaces connecting different resources. In their study on AI medical robots, Pee, Pan, and Cui (2019) showed that there are four ways to embody medical knowledge (expanding, equipping, emancipating, and growing), which leads to work transformation. Knowledge embodiment allows for automating, assisting, actuating, and augmenting part of medical personnel's work. This enables faster and more accurate diagnosis and effective communication with the doctor or patient.

Methodological approach

Research structure

We aim to explain how organizations create, integrate, and transfer medical knowledge to develop AI-based medical solutions. This is an under-explored area of research. Thus, we took an exploratory case study approach. This was a justified solution as the study met all criteria defined by Yin (2013) for that research method: explorative research questions, lack of control over events in the studied area, the focus of the study on a contemporary phenomenon within a real-life context, and unclear boundaries between the phenomenon and the context.

We put resource interaction at the core of our research design. Thus, the units of analysis were resources, activities to combine them, and involved actors. As value co-production involves subjective comprehension, we adopted an interpretative research design to identify actors' meanings and intrinsic experiences (Wieczerzycki & Deszczyński, 2022). We anchored the theory in the empirical evidence to thoroughly comprehend the study issue. We spoke with practitioners in their respective disciplines and roles in producing AI-based diagnostic systems to learn how they interact with their jobs (Sandberg & Tsoukas, 2011).

Case study selection

Considering the research questions, we looked for a case study following the criteria of (1) a company that developed AI-based diagnostic medical solutions and owned them, (2) a company that had to integrate medical knowledge that was previously not codified in the explicit form, (3) company that offered such solution to different markets and generated income for at least one year. After screening the databases and the market, we selected StethoMe, the developer of the medical AI-based application, as the empirical context for this study. This case offers an unprecedented opportunity to observe the value of co-production in two dimensions, i.e. advanced medical diagnosis and communication with users.

StethoMe invented a medical solution to identify abnormalities in the respiratory system and perform lung auscultation fully interactively. The system is based on AI algorithms cooperating with a wireless stethoscope and a dedicated application. Thanks to the mobile application, the patient can conduct the auscultation independently. Next, the obtained results pass through machine learning algorithms in search of irregularities in the respiratory system. The patient can record health monitoring status, send it to the doctor, and make an online visit via telemedicine. Thus, this is an eHealth solution (Wong, Ho, & Tsui, 2017). It took five years to develop the solution, consisting of IT, acoustic, pulmonary, and user application components. The production of an AI-based medical system requires the cooperation of many actors in an ecosystem. In the initial commercialization period of the idea, mobile stethoscopes were introduced to some hospitals and medical facilities, including departments specializing in COVID-19 treatment and ambulances. The StethoMe solution is available on the market (e.g. in Apple iStore), and its value for end-users has already been studied (Gaczek *et al.*, 2022; Emeryk *et al.*, 2023). However, we focused on how it was co-produced.

Data collection

We used multiple methods and sources of evidence to triangulate data (Yin, 2013). To collect primary data, we conducted semi-structured interviews, which focused on the process of integration of resources, roles in working on/with AI, and value co-production. Unlike many studies, we did not focus only on the company-client system but analyzed various stakeholders and their involvement in the co-production process. To verify interviews, confirm the information, and find inferences, we used multiple secondary sources and documents in addition to interviews. We analyzed articles, including articles published in scientific journals and material focused on StethoMe available online. Furthermore, to understand patients' attitudes to AI recommendations in medicine, we conducted research in the consumer laboratory. Table 2 lists the informants cited in the case description and the other data sources.

Data analysis

We elaborated multiple phases of the analytical process to analyze qualitative raw data, i.e. initial reading, developing codes, and identifying emergent themes. First, we studied data to find the descriptive codes and operational definitions of value and its creation when applying digital technologies (Jayashankar, Johnston, Nilakanta, & Burres, 2019). Analyzing the value,

Table 2. Data source and use

Source	Type of data	Use in the analysis
Interviews	3 In-depth interviews with managers of departments: machine learning (R_ML), Acoustics (R_A), Product Development (R_PD) 3 IDIs with top management: Chief Executive Officer (R_CEO), Chief Technology Officer (R_CTO), Chief Operations Officer (R_COO) All interviews lasted 60–90 minutes and were audio-recorded and transcribed	Gathering information about the co-production mechanism of AI-based solutions
Scientific papers	Five articles in high-ranked journals and two conference articles written by employees working on AI-based medical solutions	Gathering more software- and algorithm-specific information
Patients	Primary research in a lab	Identifying patient attitudes toward medical AI recommendations
Other sources	Company website, StethoMe's presentation at the TEDx conference, available media publications, interviews, and papers in the press	Understanding the context of the company and AI-based solution
Seminar	Follow-up seminar with five respondents from StethoMe	Evaluating the information collected and the research results obtained

Source(s): Authors' own elaboration

we respected Balta *et al.* (2021) and Gaczek *et al.* (2022) two-dimensional approach to AI-based value in the medical context. First is the algorithm that delivers diagnosis based on AI predictions and recommendations. The second is the AI-based system that communicates with patients using AI technologies. While analyzing the value of co-production, we focused on how this process appeared and why it proceeded that way (Massi *et al.*, 2020). The outcome of the first stage of coding was a list of value elements and co-production aims.

In the second stage, we segmented data regarding the data-driven scheme. We checked if data describing elements of value and co-production aims could design patterns related to actors, resources, and activities. At this stage, we adopted Paschen *et al.* (2020) approach to qualitative study on digital value creation. First, we applied the service-dominant logic to analyze how the operand and operant resources were integrated into value co-production (Prenkert *et al.*, 2022). Then, we followed the actors-resources-activities (ARA) model (Håkansson & Johanson, 1992) to identify what activities were run while integrating resources and what roles different actors played in value co-production (Royo-Vela, Leszczyński, & Velasquez-Serrano, 2022). Finally, we tried to understand how resource integration led to value generation.

Using a dual-coder technique, two authors were responsible for designating each value element to the ARA model's proper element. They acted as the first and second coders, respectively. Each coder divided the dataset into categories. The two coders then compared the attribution. The first and second coders' conversations continued until they understood how resources, actors, and activities affected the co-production value.

Findings

Meanings of value co-production

The respondents highlighted several insights about the nature and understanding of collaboration in developing medical AI. Interdependence among actors and teams is a crucial aspect of co-production. Each team relied on the others to successfully integrate data and tacit knowledge and achieve the project's business aims. They emphasized the necessity of frequent communication and iterative processes that involved continuous testing and feedback loops. Teams learned from each other by analyzing specific cases, primarily when unexpected results occurred. This process helped in mutual understanding, defining expectations for AI, and refining the AI system.

Another aspect of co-production was integrating the diverse expertise of physicians, acoustic engineers, and IT and AI programmers, translating physicians' subjective knowledge, and describing the results of auscultation into digital data that the AI could process, which required extensive discussions and agreements to align actors' different approaches. These also needed to overcome the challenges of different work cultures and methodologies. Physicians are accustomed to direct interactions with patients, acoustics work in isolated labs, and IT people work with digital representations of the real world. Co-production means bridging these gaps.

> Physicians have some skills but cannot always give us the information we need. Acousticians know the latter, and physicians know the former. It takes a lot of discussion to bring this together, and there is a lot of some kind of common understanding (R_CTO).

Moreover, respondents also interpreted value co-production as continuous, repetitive interactions. They described clear and structured communication and defining roles and responsibilities as essential aspects of collaboration that help streamline the process and allow all actors to know who is accountable for different aspects of a complex project.

Value co-produced in the case of StethoMe

StethoMe solution includes two main components. The first is an algorithm for accurately detecting pathological breath phenomena in auscultatory recordings (Grzywalski, Belluzzo, *et al.*, 2019). Respiratory auscultation is highly subjective. It depends on the physician's ability to interpret the sounds based on their psychoacoustical characteristics. Meanwhile, the StethoMe system provides an objective tool for detecting respiratory phenomena. StethoMe AI is a neural network architecture. It is a specialized network suitable for continuous and transient sound event detection (Grzywalski, Szajek, *et al.*, 2019). The gathered data from a blind test (we compared the results provided by a group of doctors and an AI algorithm) show that machine learning-based analysis is more efficient in detecting and discriminating respiratory sounds than a first-contact doctor. We identified it as the "diagnostic algorithm" for further research. A respondent described this component as follows:

> It was not an idea "let's use AI for something." It was the idea "let's solve the doctors' problem." This was our value. We knew the technology and could select the appropriate technology for a given problem. . . . From our perspective, we solved a physical problem, not a medical one. We do not diagnose any disease; we only check what sounds are in the lungs, name these sounds, and indicate that they may indicate a disease. Of course, this has medical consequences (R_CEO).

The second element was an AI agent that interactively guides the end-user through the auscultation process and explains the results to medical staff and patients. It consists of a digital stethoscope, a mobile application that helps the user to auscultate themselves, and an AI agent that communicates the results, allowing the patient to perform the test independently without a doctor's intervention. We identified it as the "value of AI-based medical system" for further analysis. For doctors, the value of the StethoMe solution means improving efficiency, saving time, and focusing on the patients who need care, as in many situations, the patient goes to the doctor only to get assurance that they are healthy. Two statements reflect it:

> Doctors using Artificial Intelligence will replace those who do not use it. . . . The purpose of StethoMe is to enhance the doctor's workflow, and that's what our value proposition is all about (R_CEO).

> We have feedback from doctors who described the results for us. They say that working with us improves their skills tremendously by having them describe and verify each other, then look at what the algorithms have learned and compare it with their diagnosis (R_DEV).

Regarding patients [1], StethoMe allows constant control of their health, minimizes the number of visits to a medical facility, and reduces some costs as the patient does not have to see the doctor with a positive diagnosis [2]. For hospitals, StethoMe delivers value by relieving doctors. In the case of the COVID-19 pandemic, an additional aspect due to the lack of physical contact between the doctor and the patient is the safety of the hospital's employees.

Resources integrated for value co-production

In the development of the diagnostic algorithm, operand resources were data recorded from the examination of internal sounds of the lungs (Table 3). Appropriate features of such acoustic data sets (volume, complexity, and variety) enabled machine learning to recognize auditions that indicate disease. An innovative stethoscope was necessary to obtain this data by auscultation, recording, digitalization, and wireless data transfer. Collecting such data from more than 6,000 natural and 10,071 artificial/synthetic recordings was essential. StethoMe converts this data into information about the patient's health thanks to the operant resource: (1) data collection and description procedure system that allows distinguishing between sounds indicating a pathological state from other physiological sounds (Grzywalski, Belluzzo, *et al.*, 2019), (2) acoustics knowledge, (3) pulmonological knowledge. This resulted in a digital sound pattern indicating undesirable lung changes. The algorithm recognizes such a pattern, analyzing the subsequent recording based on a description developed by a panel of physicians in the recordings' dataset used for AI training. It allowed AI to verify the additional pathological sounds and, on this basis, continuous (machine) learning (until it is frozen for certification).

Table 3. Identified resources, activities, and actors

		Diagnostic algorithm	AI-based medical system
Resources integrated			
Type of resource	Operand	Data from doctors' patients Stethoscope Machine learning	Stethoscope Artificial intelligence (set of data and algorithms to analyze this dataset)
	Operant	Data collection software Data description system Acoustic knowledge Pulmonological knowledge	Users' feedback Technological knowledge Design knowledge Smartphone application for device users
Processes integrating resources			
Type of process	Co-production process	Data collection Training of AI (machine learning) Certification Data collection	Product development
	Business development	None	Acquiring the medical community Adjusting the product to the needs of users Analyzing user needs
Actors involved			
Actors	Medical actors	The data provider (Specialist pulmonologist) Validator (Specialist pulmonologists)	Users (General Practitioners, Patients, Medical companies) Influencer in the medical sector
	Integrators	Data processor (Acoustics, IT, ML, Software specialists) Boundary spanner (Scientific leader, Key account manager) Quality Controller (Regulator, Certificate Bodies)	Designer (App developers, UX analytics, Suppliers, Device designers) AI Boundary spanner (Customer service, Product development, Scientific leader)

Source(s): Authors' own elaboration

The presented resource integration took place until obtaining certification. Accreditation was mandatory as the company positioned this solution on the market as medical equipment. Joining the certification process, machine learning was frozen as regulatory bodies prohibit online learning algorithms (Ebrahimian *et al.*, 2022). From that moment, the stethoscope and algorithms became part of the system available to the patient and doctor. These operand resources allow the patient to auscultate the chest independently and receive a diagnosis from the AI. Their doctor gets a record of this auscultation and AI suggestions without contacting the patient. For doctors, verifying their diagnosis with information from the algorithm adds value and allows them to improve their competence, as the following opinion reflects:

> Doctors who describe records for us find that working with the algorithm has improved their skills tremendously as they confront their diagnosis with AI's output (R_CTO's).

However, these operand resources require three essential operant resources for co-producing value with patients and physicians: (1) the technical knowledge of the suppliers of stethoscope components, (2) the knowledge that allows for designing a functional, comfortable stethoscope, and (3) a smartphone application that supports self-listening by the patient. The effective integration of these operant resources ensures a user experience that yields data of sufficient quality for AI diagnosis during a listening session.

Activities for resource integration

We can distinguish several processes integrating resources and divide them into two groups (Table 3). The first group is co-production and it includes data collection, AI training, certification, and product development. These processes focus on the critical outcome, i.e. the delivery of the diagnostic algorithm. The second group, business development, has supportive functions and covers analyzing users' needs, acquiring the medical community, adjusting the product to the user's requirements, and analyzing the market. In turn, these processes are more significant for the co-production of AI-based medical systems.

The first step in co-production of an AI-based solution is data collection for the technical department (acoustics, ML, software). This requires cooperation with involved doctors, equipping them with a dedicated software system for collecting data and teaching them how to describe auscultation. In the next step, acoustics process the data in the laboratory. Finally, the filtered data goes to the machine learning process. The AI software receives training data sets that include the inputs and the correct outputs and it learns in several interactions. This process utilizes error checking and medical counseling. Respondents presented this process as follows:

> Doctors have certain skills but cannot always give us the necessary information. The point is that they are used to having the device, being with the patient, and performing tests. We are used to having sound in digital form. We can recreate a sound and visualize it on computers. To combine those worlds, we need a lot of discussions, common arrangements, and finally, an interface that transfers a doctor's auscultation to digits (R_A).

The process of AI training lasted until achieving a marginal increase in effectiveness with the increase in data. Then, the concilium of acoustics and doctors (pulmonology specialists) positively verified the descriptions. This stage aimed to create a credible and reliable system that can describe the quality of AI's measurement and diagnosis. This process is as follows:

> At least three doctors had to agree on the description of a given recording for us to consider it a correct description. This is our gold standard. We have the same recordings described by each of these three doctors and a description made by a neural network. Then, we look at how much these descriptions differ from each other. We noticed that these descriptions differed between doctors initially, and our algorithms were in the middle. The description of the algorithm is more similar to each doctor individually than between different doctors. This proves we cannot achieve much more here because the doctors are inconsistent (R_ML).

When actors developed an innovative acoustic device, an intelligent stethoscope, they were involved in working on a mobile application, stethoscope software, and doctors' platform. This process investigated the device design and production, software integration, and user experience to ensure ease of use.

Business development processes oriented toward relations with the medical world, i.e. building relationships and credibility among doctors by visiting and presenting solutions at medical conferences and analyzing legal, technological, and financial factors. Moreover, development processes aimed at adjusting the product to users' needs. They included obtaining feedback from commercial companies that conduct pilot programs and doctors, i.e. the system's final users.

Actors' roles in resources integration

Actors from various fields created StethoMe (Table 3). They played roles that we may assign to two groups: medical staff and integrators. The first group was crucial for the project because of the intended use. In resource integration, doctors play many roles in the co-production of value: family doctors provide data, and specialists evaluate data and validate the algorithm. As users of the solution, physicians offer feedback. Finally, the assigned doctors, who played the role of influencers, authorized and promoted this solution in the medical world.

On the other hand, the process utilized an integrator to launch processes that allow data obtained from doctors to be processed into a medical AI solution. The acoustic underwent processing by acoustics, IT, and machine learning specialists involved in AI training. The positive effects of their work allowed the actors responsible for quality control to start work. These were people writing scientific articles and verifying the quality of the solution from the medical point of view and certification organizations.

Artificial intelligence is an essential element of the described medical solution. Its final shape results from the cooperation of various actors with capabilities in product design, user experience design (UX), and production. Moreover, they had to combine suppliers' recommendations with potential partners from the healthcare ecosystem who defined their expectations in terms of functionality. The following opinion reflects the roles' complexity:

> We had a shared vision of how we wanted to see these products and what we were creating, . . . We knew that one of the roles we were missing was a product and company image designer. We also needed a person to embed us in science – in acoustics and medicine. We also needed electronics to make a good device. We had a good machine learning team because we had previously worked on image recognition technology. We also found a person developing mobile applications, thanks to which we did not focus on the finished product but on mobility (R_COO).

The certification confirmed the integration of the value of the diagnostic algorithm. Hence, the certification body played the third-party role between a company that developed the AI-based medical system and its users. Boundary spanners participated in integrating resources for diagnostic algorithms and the medical system. They built and maintained relationships with the medical community to collect data from doctors, gather user feedback, and establish credibility among doctors.

Discussion

Value co-production in the medical context

The findings show the interpretation of value co-production in the context of AI-based solutions (RQ1). People perceive it as complex because of the interdependence of diverse actors collaborating. They combine diverse tacit and explicit knowledge, cultures, methodologies, and even ways of interpreting the work and resources. Respondents had a unified understanding of those differences and ways of dealing with them by regular communication to explain actors' expectations and aims. We did not identify the avoidance of responsibility in allocating it to a solution provider, which Saha *et al.* (2022) suggests is the feature of value co-production.

Actors distributed responsibility among them because of their significant involvement in the value of co-production and motivation to develop AI-based medical solutions.

We identified the value as the outcome of co-production in two dimensions, namely the medical algorithm that delivers diagnosis of pulmonary lesions and the AI-based medical system that end-users can use. We interpreted the algorithm from the perspective of its high accuracy and the system from the angle of excellent user experience. Although both dimensions rely on machine learning and can be developed through feedback after each interaction, regulations prevent their application to medical equipment. This contradicts the findings of Latinovic and Chatterjee (2024) in the case of orthopedic products, who state that value can still be improved thanks to algorithms. Moreover, Kot and Leszczyński (2022) found that AI-based value is dynamic and fuzzy in the case of conversational agents. This presents the difference between medical and non-medical AI-based value.

Our analysis also showed that all actors should be aware that the outcome of their co-production study requires implementation in the healthcare system. To achieve this, legal requirements must be met by certification, and engaging activities are essential for involving patients and physicians in using AI-based medical solutions. Rational arguments can work (cost, time, risk reduction), and hospitals and clinics can also consider using AI to automatically prioritize sick individuals in their triage guidelines (Fernandes *et al.*, 2020).

As we identified two dimensions of value, the sections below discuss the answers to the research questions on what resources are integrated (RQ2), how it happens (RQ3), and who is involved (RQ4).

Co-production of the medical diagnostic algorithm

This study presents exciting findings from the medical field, where the co-production of medical diagnostic AI is a complex, multi-step process due to the integration of resources. A vital aspect of this process is knowledge embodiment. When auscultating patients, physicians refer to their experience, their interpretations of sounds, and their tacit knowledge. Researchers must generate an interface to digitalize that tacit knowledge and translate it into a language that machines can understand. This interface is an operant resource, which makes it possible to decode data interpretations (operand resource). To make this possible, IT staff developed a tool for collecting auscultation data and creating an ontology representing doctors' tacit knowledge. We applied this ontology to design learning algorithms and then to train them by diagnostics performed by acousticians and medical specialists. This focus on data quality confirms its importance for predictions delivered by AI (Sambasivan *et al.*, 2021).

We explored medical, acoustic, and IT specialists' roles in co-producing a medical diagnostic AI around a patient's needs by incorporating complex resources in the healthcare ecosystem. Transferring knowledge between stakeholders requires coordination, mutual learning, and building trust. One of the essential roles belonged to doctors who gathered data at the beginning of the AI learning process with acoustics and then controlled the recommendations of trained AI. Building mutual trustworthiness between doctors, acousticians, and IT specialists became essential. The motivation of actors to invent usable and helpful solutions was vital to enhance the knowledge exchange facilitated by developed technology. However, the integrator's role might become the critical determinant in the successful value co-production. This finding supports Carrillo, Edvardsson, Reynoso, and Maravillo (2019) proposition that shared values among engaged actors enable knowledge sharing and mitigate value creation.

The case study showed that the solution provider is vital even if several different actors are involved in the healthcare market. It coordinated the collaboration of several actors to create a medical solution for end-users and took responsibility for the outcome. This is in line with Laurisz, Ćwiklicki, Żabiński, Canestrino, and Magliocca findings (2023) on the responsibility shift to suppliers in the healthcare market. StathoMe is a medical diagnostic AI. Therefore, it requires certification before launching in the market. We observed the borderline between diagnostic AI and medical solutions. The development of diagnostic AI had to be completed for certification before developing and commercializing the medical solution. A certificate freezes the learning process and eliminates the risk of erroneous data in the future. This contrasts with the Leone *et al.* (2020) study on AI in healthcare, where different aspects of value were blurred.

Co-production of the AI-based medical system

The value of an AI-based medical system relates to the servitization of a stethoscope. The analyzed case study showed the digitalization process of this well-known tool for auscultation. Its value is related to AI-based services recommending treatment and imitating a doctor's hearing system and the doctor's ability to detect pathological sounds.

It was essential to provide users with the right experience with the application and device that would translate to their satisfaction regarding the ease of use and communication of the obtained results and related recommendations. In healthcare, the design of services and patient experiences is still under-researched and rarely used by entities providing medical assistance (Patrício *et al.*, 2020). Clients receive service value through interactions. Therefore, the user experience design was an essential factor that could translate into the positive evaluation of the usability and functionality of the StethoMe AI-medical solution.

The UX designers were shaping the AI recommendations needed for designing human-machine interfaces and communication methods, which can affect the level of acceptance for recommendations delivered by autonomous technologies (Gaczek *et al.*, 2022). Therefore, collaboration with UX designers and app developers aimed to secure functionality and increase the trustworthiness of AI's recommendations.

The case of StethoMe shows that we may also consider the system's value from the angle of imitating human actors by AI. The AI algorithm might be a boundary object human actors apply to co-produce value. Moreover, we can also discuss it as a new, non-human actor interacting with others to analyze human health and provide medical recommendations Kot and Leszczyński (2020). However, if we perceive systems as actors, approval and control will be referred to themselves, which have significant consequences in the medical context (Meskó, Hetényi, & Győrffy, 2018).

Conclusions

Theoretical contribution

Our study offers several contributions to the management literature. First, it enriches the literature on value co-creation by presenting insights into subjective comprehensions of value co-production. Co-production is linked with the interdependence of actors, integration of diverse expertise, work cultures and methodologies, structured communication, and defining actors' roles and responsibilities. Second, it contributes to the literature by exploring resources integrated when professional actors co-produce a digital solution. It presents how knowledge, as an operant resource, can transform resources and build interfaces between operand resources to meet the analytical requirements of AI. It also adds to the discussion of Sklyar, Kowalkowski, Sörhammar, and Tronvoll (2019) on the various roles that technology plays in dealing with the complexity of digitalized systems by demonstrating how machine learning enabled the integration of previously unconnected doctor data. We also emphasized how AI can generate knowledge integration patterns with profound implications for value co-production (Hartmann, Wieland, & Vargo, 2018).

Third, this study contributes to the knowledge management literature by highlighting the powerful aspects of digitalized knowledge in value co-production. Our research explored converting tacit knowledge from doctors who auscultate patients into explicit, codified acoustic knowledge. We showed that AI learns by combining data collected in medical examinations with ontologies used to describe that data. Scholars have already identified the importance of knowledge as a resource in business (Tronvoll, Sklyar, Sörhammar, & Kowalkowski, 2020) and the medical context (Abbariki, Snell, & Easterby-Smith, 2017). We add to this literature by showing that in implementing AI in healthcare, knowledge

Table 4. Practical implications for co-production of AI-based medical solution

Area	Pathways	Managers' activities
Integration of resources	1. Preparing a tool to translate actors' medical tacit knowledge to explicit data 2. Gathering data from physicians 3. Transforming analogue data to digital form 4. Using AI machine/deep learning algorithms to find patterns in a dataset	1. Gather actors who have high-quality medical data 2. Provide physicians with training on how to use the data translation tool 3. Find the best physicians to establish the gold machine/deep learning standard 4. Implement protocols to protect patient data in compliance with legal regulations
Engagement of interdisciplinary teams	1. Involving physicians that are in everyday contact with patients, best doctors 2. Involving IT specialists, acoustics, and AI programmers 3. Creating a team of user experience designers and interface specialists	1. Organize meetings for interdisciplinary teams to share knowledge and experiences 2. Conduct training sessions to help actors understand the specifics of others' work 3. Implement a project management tool to facilitate collaboration and communication
Development of medical solution	1. Defining the reference point for AI accuracy 2. Designing intuitive interfaces for physicians and patients 3. Creating a feedback loop where users can report issues and suggest improvements	1. Define quality standards 2. Involve UX designers from the early stage of development 3. Use prototypes and iterative testing 4. Regularly collect feedback from physicians and patients
Certification and regulatory process	1. Having the necessary technical and medical documentation required for certification 2. Conducting clinical tests and validating AI algorithms 3. Submitting applications to relevant regulatory bodies	1. Identify certification bodies 2. Create a team responsible for preparing and managing the certification process 3. Utilize regulatory consultants to ensure all legal requirements are met. 4. Stay updated on regulatory changes regarding AI in medicine and adjust procedures accordingly
Value delivery for the healthcare system	1. Involving patients in a treatment process 2. Convincing patients and physicians to reduce unnecessary f2f visits 3. Educating physicians for trusting and using trusting AI-based solutions	1. Enable automatic decision support system (e.g. triage) 2. Prepare case studies and calculations of time and cost reductions for the healthcare system and patients 3. Prepare materials on the reduction of hospitalizations by permanent monitoring of treatment and fast reactions to changes

Source(s): Authors' own elaboration

embodiment is crucial for machine learning as this technology is based on highly codified data. In a broader context, we confirmed Ferraris, Mazzoleni, Devalle, and Couturier (2019) suggestion that through knowledge management, AI can detect patterns to solve problems.

Finally, this study contributes to the discussion on AI-activated value by highlighting two interconnected dimensions: the predictive power of machine learning and the AI's ability to provide acceptable recommendations to its users. That is in line with value dimensions found by Rong, Mendez, Bou Assi, Zhao, and Sawan (2020), Samuel, Kashyap, Samuel, and Pelaez (2022) and Gaczek *et al.* (2022). We also highlight that in the case of medical applications, AI has to be stable and understandable when launched to the market.

Managerial implications

Our article offers direct implications for managers who want to create a medical AI. Our case study reflects the complexity of the healthcare ecosystem with various stakeholders. The co-production process requires the involvement of actors from different fields with diverse but fragmentary specialist knowledge and activities that enable the flow of knowledge between individual actors. Managers can learn from our insights the combination of resources and actors to manage strategic value co-creation that allows for co-production process harmonization. For instance, the importance of doctors is undeniable. However, their roles and related activities may vary depending on their knowledge and experience. Building and developing a relationship with doctors allowed their engagement and openness to share knowledge. In the future, they will also become brand ambassadors.

Our observations can guide managers working on AI-based solutions to transform knowledge into a medical system with AI. For example, the codification of tacit knowledge held in doctors' heads, integration, and conversion into a marketable product was a complex process, finished with the certification. Table 4 presents pathways and related managerial activities in five areas: integration of resources, engagement of interdisciplinary teams, development of medical solutions, certification and regulatory process, and value delivery for the healthcare system.

Limitations and future research directions

We based this research on a single case study when the co-production of the AI-based medical solution occurred. Thus, further development could include other medical sectors in which AI is emerging. As we focused on the co-production process and the provider's perspective, we did not include final users in our research (presented by Gaczek *et al.*, 2022). Furthermore, this study showed a new aspect of the actor's role in value co-creation: the emergence of non-human, AI-based agents (Paschen, Paschen, Pala, & Kietzmann, 2020). Artificial intelligence, which acts as an integrator of knowledge and a part of medical solutions, was even perceived as a "new doctor." This raises many concerns based on the uncertainty of how the algorithm works (Samek, Wiegand, & Müller, 2017) and doctors' fears of being replaced by AI (Cave & Dihal, 2019). Such concerns are essential in the medical domain, as professionals need to understand the basis of decisions that AI-based systems make.

Notes

1. The detailed value for patients of StethoMe was presented by Gaczek *et al.* (2022).
2. In instructions for use, StethoMe company always suggests contacting the doctor if a patient worries about their symptoms.

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