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AI-enabled smart manufacturing boosts ecosystem value capture: The importance of servitization pathways within digital-intensive industries

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ABSTRACT

Understanding successful pathways for manufacturers to capture value within the service ecosystem framework is a recent and still nascent area of research that requires further investigation and growth. Within industrial settings, artificial intelligence (AI) constitutes an enabling technology that can be integrated across a network of products and systems, driving the transformation of these service ecosystems. From this perspective, this study proposes that the symbiotic convergence between AI-enabled smart manufacturing, which facilitates process and product enhancements, and servitization, which enables product availability and customization, contributes to a higher level of ecosystem value capture. To address this issue, a research model employing Smart Partial Least Squares was developed to examine the interplay between these constructs. By using survey data from a purposively selected sample of servitized manufacturing firms, the findings reveal the synergistic effects of integrating AI-enabled smart manufacturing and servitization. Furthermore, the results indicate variances across industrial sectors, and highlight that in digitally-intensive industries, service business models have undergone more substantial transformations, fostering accelerated ecosystem development streamlined by customization. Conversely, in digitally-augmented industries, where inputs are digital but products are predominantly analog, digital capabilities are primarily confined to production processes.

1. Introduction

While the emergence of Industry 4.0, which integrates technologies such as the Internet of Things (IoT), big data analytics and cloud services (Culot et al., 2020), has become a current, central topic in the management and engineering fields (Frank et al., 2019; Saporiti et al., 2023), the concept of artificial intelligence (AI)-enabled smart manufacturing remains relatively unexplored in industrial settings. AI employs computational agents to address intricate and time-consuming computational challenges intelligently (Burström et al., 2021; Mikalef et al., 2023), while smart manufacturing encompasses a suite of tools designed to oversee manufacturing operations, manage data transmission within the corporate and business ecosystem, establish continuous operational monitoring systems, and to create mechanisms for problem identification and prediction (Tao et al., 2018; Wamba and Queiroz, 2022). Prominent firms exemplifying AI application in conjunction with smart manufacturing include Tesla, renowned for its quality control system adept at swiftly identifying vehicle flaws. Toyota also stands out for its use of AI to optimize the supply chain, while Bosch streamlines processes and automates repetitive tasks by means of robotic process automation (Li et al., 2018). Airbus, on the other hand, implements AI in its production line optimization system (Ransbotham et al., 2017). Both AI and smart manufacturing technology systems are growing in importance in terms of market size –AI had a market size of $515.31 billion in 2013 and is expected to reach $2025.12 billion in 2030 (Fortune Business Insights, 2022)– and have gained dramatic managerial importance. Smart manufacturing has ushered in a new era of competition (Porter and Heppelmann, 2014).

Smart manufacturing has emerged as a facilitating factor that helps manufacturers engage with and leverage potential opportunities during the transition to servitization (Xing et al., 2023). Servitization entails the digital transformation of manufacturing firms as they transition toward a service-oriented business model (Bustinza et al., 2024; Khan et al., 2024; West et al., 2018). In the literature on servitization, smart

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manufacturing constitutes a novel manufacturing paradigm characterized by networking and service orientation (Bustinza et al., 2022; Lafuente et al., 2023) which has evolved from traditional manufacturing and service modes, and encompassed and extended them by seamlessly integrating a wide range of advanced technologies (Ren et al., 2019). The foundations of servitization suggest that the "smartness" conferred by smart manufacturing systems is not solely contingent on the sheer number of new technologies incorporated, but rather on their co-creation potential (Vargo and Lusch, 2017; West et al., 2018), which produces a symbiotic effect. Smart manufacturing involves the smooth integration of cooperative manufacturing systems that can dynamically adapt to changing demands and conditions in the factory, throughout the supply network, and in accordance with customer needs in real-time (Moghaddam et al., 2018; Potter et al., 2015). Considering the importance of real-time in service provision, there are ongoing initiatives to transform real-time data into practical decisions by actively exploring the potential of combining AI methods with smart manufacturing principles and technologies (Chien et al., 2020; Mikalef and Gupta, 2021). Consequently, the servitization literature upholds that the interactive effects of a broader range of digital technologies and servitization on performance must be revealed (Kohtamäki et al., 2020; Yang et al., 2023). The research herein aligns with these pertinent initiatives by providing a novel analysis into the influence of a specific technology, AI-enabled smart manufacturing, on a distinct outcome; namely, ecosystem value capture. The significance of this analysis is underscored by the fact that a substantial number of organizations continue to face challenges when it comes to harnessing the potential value from their AI investments (Fountaine et al., 2019). This issue is particularly acute in the field of servitization, where efforts are still being made to understand the potential mechanisms for value generation from such technologies (Chen et al., 2021).

While the majority of AI-enabled smart manufacturing implementations in organizations are associated with service improvements and updates, the need remains to comprehend how value is captured (McKinsey, 2023). This issue arises from the fact that servitized manufacturers operate and compete within complex ecosystems consisting of various suppliers, distributors, partners and customers (Chen et al., 2021), which promotes the emergence of new value-adding service innovations on a global scale (Vandermerwe and Erixon, 2023). Within these ecosystems, interdependencies and alignments between processes are established, as members aggregate around the central value propositions (Sklyar et al., 2019). These interdependencies vary depending on the industry context, as highlighted by Pathak et al. (2020); an aspect that has received limited attention in servitization literature (Bustinza et al., 2019). To address the identified gap, this study builds on the axioms and foundational premises of the service-dominant logic (SDL), which posits that service is the fundamental basis of exchange. Within this framework, actors (e.g., individuals, firms, organizations, customers, etc.) are viewed as resource integrators who collaboratively create value (Lusch, 2011; Vargo and Lusch, 2017). This perspective highlights that value co-creation involves all social and economic actors and is most effectively examined at higher levels of aggregation, such as meso- or macro-levels, rather than focusing solely on individual interactions (Chandler and Vargo, 2011)

At the meta-layer, exchange occurs within complex networks, introducing time and replication. Practices and processes are replicated at various levels, leading to institutionalization, which legitimizes actors within societal systems. This dynamic yet stabilizing process forms service ecosystems—loosely coupled, value-proposing networks that co-produce and exchange services (Chandler and Vargo, 2011; Lusch, 2011). These ecosystems reflect the evolving relationship between individual efforts and larger social structures. In the context of SDL, actors exchange value propositions, and the co-creation of value is influenced by a variety of factors, including the environment, objectives, and strategy (Khan et al., 2024). This dynamic process underscores the necessity for continuous adaptation. AI-enabled smart manufacturing plays a crucial role in this regard by enhancing or sustaining value propositions through its ability to adapt and respond to changing conditions effectively. This framework is instrumental in recognizing that value accrues through the amalgamation of resources derived from diverse origins. It is argued here that this co-created value emanates from the establishment of service value ecosystems. This aligns with scholarly investigations delineating value ecosystems that surpass the confines of traditional supply chain conceptualizations (Chen et al., 2021). Moreover, it is concordant with prior research suggesting that value creation within these ecosystems occurs through the convergence of digital technologies and servitization (Abou-foul et al., 2021; Frank et al., 2019).

In line with this idea, a research framework comprising associated hypotheses was designed positing that the convergence of AI-enabled smart manufacturing and servitization can enhance value capture within ecosystems. Specifically, it is contended that AI-enabled smart manufacturing exerts an indirect influence on value capture through servitization, distinguishing between manufacturers operating in digitally-augmented or digitally-intensive industries. To be more precise, digitally-augmented industries comprise sectors where AI-enabled smart manufacturing primarily enhances the input aspect of production, thereby improving the provision of physical components. However, the products offered to consumers may not inherently possess digital capabilities. Conversely, in digitally-intensive industries, AI-enabled smart manufacturing is extensively leveraged throughout the entire product lifecycle, encompassing both smart and connectivity components (Porter and Heppelmann, 2015). By using data gathered from 303 responses from senior executives in the UK and Germany, a partial least squares (PLS) analysis was employed to investigate the proposed relationships. Thus, this study endeavors to address the following research questions:

RQ1. What is the direct impact of AI-enabled smart manufacturing and mediating effect of servitization on value capture within ecosystems?

RQ2. In which industrial contexts does the mediating effect of servitization manifest itself in the relationship between AI-enabled smart manufacturing and value capture within ecosystems?

Overall, this study makes several important contributions to the literature. First, it substantiates SDL as a conceptual framework to understand how servitization serves as a transformative mechanism that aligns with contemporary propositions advocating that the supply chain be renamed service ecosystems (Lusch, 2011). Second, it sheds light on the growing debate regarding the optimal configurational arrangement between digitalization, servitization and organizational benefits, and the role of servitization (i.e., moderating/mediating) in this pattern –e.g., see Davies et al. (2023), Harrmann et al. (2023), or Schulz et al. (2023). In this respect, the study updates and consolidates evidence concerning this discussion by expanding the traditional pathway approach –i.e., digitalization ➔ servitization ➔ performance, see Vendrell-Herrero et al. (2024)– and explaining the mechanisms that uphold this arrangement; specifically delving into how servitization connects AI-enabled smart manufacturing and value ecosystems. Finally, it contributes to analysis into the convergence between the AI and servitization fields by offering insights into the specific industrial contexts where servitization assumes a more prominent mediating role –a pivotal element in order to comprehend the process of capturing value within ecosystems. This is an argument that certainly posits various important insights: first, the differing use of AI-enabled smart manufacturing technologies in digitally-augmented and digitally-intensive industrial settings (Porter and Heppelmann, 2015); second, servitization in digitally-augmented industries diminish their differentiation potential compared to their digitally-intensive counterparts; third, services act as catalysts for ecosystem emergence, fostering organic evolution in industries (Kohtamäki et al., 2019); and lastly, digitally-intensive industries undergo profound business model transformations due to the prevalence of customized services, enabling ecosystem development facilitated by servitization (Bustinza et al., 2019). Altogether, this indicates that digitally-intensive industries experience more pronounced changes in business models compared to digitally-augmented industries, thereby ratifying the crucial role of services in establishing ecosystems across all industries.

2. Theoretical framework

This paper delves into the convergence of AI-enabled smart manufacturing and servitization within the framework of service ecosystems, guided by the principles of SDL. The SDL framework shifts the focus from traditional goods-dominant logic to value co-creation through service, emphasizing the role of operant resources like human skills, organizational structures, and digital technologies in co-creating value. The first section, "Service-Dominant Logic," explores how value is co-created by various actors within service ecosystems and highlights the critical role of technologies like AI-enabled smart manufacturing in enhancing value propositions and fostering direct and indirect network effects. The subsequent section, "Artificial Intelligence-enabled smart manufacturing," provides a comprehensive overview of AI and smart manufacturing, discussing their definitions, roles, and integration within manufacturing systems. It also examines foundational or base technologies such as IoT, cloud computing, and big data, which underpin AI-enabled smart manufacturing and facilitate advanced predictive capabilities and optimization in manufacturing processes. By combining SDL and AI-enabled smart manufacturing, this paper aims to develop a coherent framework that offers a deeper understanding of the interaction mechanisms between digital technologies and servitization, ultimately enhancing ecosystem value capture.

2.1. Service-dominant logic

Service-dominant logic (SDL) refers to a meta-theoretical framework to understand value creation and co-creation, where focus on value shifts from the neo-classical, production-oriented (i.e., goods-dominant [GD] logic) viewpoint to one based on service value creation (Vargo and Lusch, 2004). In essence, SDL centers on the role of operant resources such as human (e.g., skills and knowledge possessed by individual staff members), organizational (e.g., controls, routines, cultures, competences), informational (e.g., knowledge concerning market segments, competitors and technology) and relational (e.g., relationships with competitors, suppliers and customers), which are used to act upon operand resources, typically physical (e.g., raw materials) to co-create value in service provision (Madhavaram and Hunt, 2008).

According to SDL, value is determined and jointly produced by multiple actors in the service ecosystem (i.e., consumers, service providers and other stakeholders), and value co-creation only occurs when these actors actively participate in the process (rather than merely being passive recipients of value) and remain engaged throughout the service exchange, acting as resource integrators (Sun and Gregor, 2023; Vargo and Lusch, 2016). Drawing on Akaka and Vargo (2014), digital technologies can be conceptualized as operant resources capable of integrating, collaborating and accessing other resources. As a result, they prove to be important resources to revamp service delivery by means of novel processes in value co-creation (Scarlett et al., 2021; Vargo, 2018). In fact, existing research on SDL endorses the role of digital technologies as superior value-creation resources (Barile et al., 2021), contributors to enhanced customer engagement (Hollebeek and Belk, 2021), experience (Puntoni et al., 2021) and satisfaction (Gelbrich et al., 2021), and innovation processes in service systems (Blichfeldt and Faullant, 2021).

In line with the above distinction between resources, it is argued here that AI-enabled smart manufacturing alongside servitization constitute operant resources capable of materializing and mobilizing operand resources effectively from heterogeneous actors (Akaka and Vargo, 2014; Vargo and Lusch, 2004, 2008). This fosters a harmonious relational context that encourages seamless integration and interaction between actors and resources (Fang, 2019), thus enabling the emergence of new value co-creation opportunities and processes in varying spatial and temporal settings within the service value ecosystem (Chandra and Rahman, 2024; Vargo and Akaka, 2012).

Therefore, from the SDL perspective, primary emphasis is placed on integrating operant resources in order to create value collaboratively (Akaka and Vargo, 2014). According to this framework, integration is driven by technologies and servitization, and manifested in the form of ecosystem value capture (Stoll et al., 2020). Hence, anchored in SDL, an attempt has been made to take a pioneering step toward developing a coherent framework by offering a description of the underlying interaction mechanisms between AI-enabled smart manufacturing, servitization and ecosystem value capture. The conceptualization presented thereby offers a deeper understanding of this interaction when exploring the convergence between digital technologies, servitization and organizational performance (Davies et al., 2023).

2.2. Artificial intelligence-enabled smart manufacturing

The literature on AI lacks a universally accepted definition, leading to challenges to fully understand the concept. To begin analysis of this concept, the notion of "intelligence" must first be explored, which is widely understood as "… the ability of a system to act appropriately in an uncertain environment, where appropriate action is that which increases the probability of success, and success is the achievement of behavioral subgoals that support the system's ultimate goal" (Albus, 1991, p. 474). Building on this foundational understanding, one of the pertinent definitions aligning with our conceptual model is proposed by Mikalef and Gupta (2021, p. 3), who define AI as "...the ability of a system to identify, interpret, make inferences, and learn from data to achieve predetermined organizational and societal goals." This definition provides a solid framework for the conceptual model as it refrains from emphasizing human-like abilities and programing origins, and recognizes that AI applications may exhibit complementary characteristics, such as being developed and tuned by other AI systems. This definition is tailored to the study of management and information systems-related phenomena, thus facilitating the identification of AI in the organizational context (Keding, 2021).

AI plays a central role as an enabling technology in the context of smart manufacturing. AI encompasses a diverse range of software techniques aimed at equipping computers with the capacity to sense, reason, interpret, communicate and make decisions in a manner akin to human cognition (Teece, 2018). Smart manufacturing, on the other hand, is a sophisticated and fully integrated manufacturing system characterized by collaborative operations that are capable of responding in real-time to dynamic changes in demands, factory conditions, ecosystem-wide factors and customer requirements (Ghobakhloo, 2020; Kusiak, 2018). Thus, smart manufacturing is a complex and evolutionary process that entails multiple manufacturing and information technologies (Szalavetz, 2019). The convergence of AI and smart manufacturing is epitomized by the concept of AI-enabled smart manufacturing, which envisions a system where machines, products, services and human actors are seamlessly interconnected via wireless networks. These entities are continuously monitored by an array of sensors and guided by advanced computational intelligence (Tao et al., 2018). AI-enabled smart manufacturing significantly boosts a firm's capacity to navigate and position itself effectively within its broader ecosystem, as such systems facilitate the capture of crucial data, and the associated decision-making processes across the entire ecosystem (Raff et al., 2020). Furthermore, AI-enabled smart manufacturing signifies a substantial departure from traditional value chain management practices, as it has been driven by the central role attributed to data utilization as the primary source for value propositions (Jovanovic et al., 2022; Vendrell-Herrero et al., 2017).

While the existing literature has extensively explored the benefits of

AI and smart manufacturing for various activities within the ecosystem and its elements (Bustinza et al., 2022), the majority of these studies have focused solely on the direct impact on business functions (Szalavetz, 2019). AI provides the capacity to identify, interpret, make inferences and learn from data supporting smart manufacturing, thus transforming it into an advanced manufacturing system that employs sophisticated data analysis to enhance manufacturing intelligence. AI-enabled smart manufacturing is a system underpinned by a set of foundational technologies (IoT, cloud computing, big data and analytics) that facilitate different aspects such as the delivery of raw materials and product-services via smart digital platforms, supporting customer relationships, managing resources, executing systems, and overseeing product-service lifecycle management via smart manufacturing technologies. It also enhances the way in which products and services offer value through smart product capabilities (Frank et al., 2019; Porter and Heppelmann, 2014). Accordingly, AI-enabled smart manufacturing constitutes the convergence of such technologies by collectively facilitating machinery failure prediction, predictive maintenance, quality control, monitoring, and the prediction of machinery issues. It also enables connectivity across different platforms, and facilitates interactions with other objects and systems (Frank et al., 2019; Tao et al., 2018) while empowering optimization and autonomy (Porter and Heppelmann, 2014).

Frank et al. (2019) showed that the higher the level of sophistication a company attains in smart manufacturing technologies, the more pronounced the prevalence of base technologies becomes. The core components of these base technologies encompass the IoT, cloud services, big data and analytics. These technologies are recognized as foundational because they underpin and permeate all Industry 4.0 dimensions (Wamba and Queiroz, 2022) by facilitating interconnectivity and furnishing the intelligence essential for the evolution of modern manufacturing systems. The IoT comprises a complex network of interconnected devices attached to various objects or subjects. These devices are equipped to gather data pertaining to both internal and external variables associated with said objects or subjects. Subsequently, they engage in analysis of the data, its transmission, and then carry out actions based on the data analysis, all within defined objectives and constraints (Singh and Bhanot, 2020). These devices possess the capability to transmit and analyze data in both localized environments and from remote locations, all whilst adhering to pre-established conditions that the actors must consider, including limitations in resource availability, privacy concerns and security considerations (Goumagias et al., 2021). The data generated by this process enables unprecedented interactions between physical and digital entities, thus fostering value creation in terms of cost efficiencies and perceived utility. Furthermore, the IoT gives rise to novel isolation effects, which spread across individual, organizational and societal levels, and ultimately contribute to the transformative impact of IoT technologies (Tao et al., 2018).

Cloud computing proves to be a novel computing paradigm, characterized by its provision of scalable, on-demand and virtualized resources for users. It allows users to access a shared pool of computing resources with minimal management effort. However, there are notable challenges and concerns associated with cloud adoption (Ghahramani et al., 2017). Cloud services enable on-demand network access to a shared pool of computing resources, and facilitate data storage with internet servers and remote access. This technology promotes the integration of diverse devices by eliminating the need for physical proximity, whilst enabling seamless information sharing and activity coordination (Wang et al., 2019). Cloud services encompass resources and applications delivered via the Internet or cloud computing platforms, which facilitates the connection of different equipment, and results in big data collection (Frank et al., 2019). Big data plays a crucial role in modern industrial processes by collecting data from various sources, including sensor readings, and employing analytical techniques such as data mining and machine learning (Hyun et al., 2023). It is recognized as a primary catalyst for the fourth industrial revolution, offering a significant competitive advantage from the insights it yields. Big data is indispensable for creating digital replicas of manufacturing facilities (digital twins) and supports advanced predictive capabilities, allowing the identification of potential disruptions in production before they occur (Frank et al., 2019). It serves as the cornerstone of smart manufacturing, enabling the collection and processing of vast amounts of production data via universal interfaces such as IoT gateways, thereby unlocking the potential for enhanced intelligence and innovation in manufacturing processes (Tao and Qi, 2017).

3. Hypotheses development

The following section delves into the intersection of base technologies and AI-enabled smart manufacturing, exploring their synergistic integration. We begin with an examination of the Internet of Things (IoT), cloud computing, and big data analytics, highlighting their role in enhancing decision-making and forming the foundational infrastructure of smart manufacturing systems. The discussion transitions into AI-enabled smart manufacturing and its contribution to exchange value propositions. Here, we delve into how digital advancements drive transformation across industrial sectors, focusing on servitization and its role in co-creating value within ecosystems. The interplay between AI-enabled smart manufacturing, servitization, and sector-specific contexts is critically scrutinized to understand their collective impact on value generation. This section posits that Industry 4.0 technologies significantly enhance smart manufacturing capabilities, facilitating ecosystem value capture through service-oriented models. The subsequent hypotheses and conceptual framework aim to provide a comprehensive understanding of these dynamics, offering insights into how industrial manufacturers can strategically leverage these technologies and servitization to achieve ecosystem value capture. To support readership and flow of arguments Table 1 provides definitions for key topics and concepts used in this section.

3.1. Base technologies and AI-enabled smart manufacturing

The synergistic integration of the IoT as a network comprising interconnected devices, cloud services coupled with computing infrastructure, and the use of big data and analytics emerges as a crucial driver for enhancing decision-making in diverse facets of industrial enterprises (Frank et al., 2019). Collectively, the IoT serves as a foundational infrastructure in which cloud services function as the underlying computational engine, while big data serves as a valuable resource (Aryal et al., 2020). This interconnected system empowers users to leverage standard capabilities for the efficient processing of distributed queries spanning multiple datasets (Hashem et al., 2015). The timely retrieval and presentation of resultant datasets can be used to facilitate and streamline the decision-making process (Gopal et al., 2024). Considering that the integration of these Industry 4.0 base technologies supports smart manufacturing (Bustinza et al., 2022; Frank et al., 2019; Tao and Qi, 2017) as well as AI-enabled systems (Caiazzo et al., 2023), it is posited that:

H1. Industry 4.0 base technologies positively relate to AI-enabled smart manufacturing.

3.2. AI-enabled smart manufacturing and value capture ecosystems

The rapid advancement of digital technologies is driving significant transformations in various aspects of industrial ecosystems, including products, services, innovation processes, business models and overall business operations (Kolagar et al., 2022). Industrial manufacturers are increasingly embracing servitization through ecosystems (Davies et al., 2022; Kohtamäki et al., 2019; Vandermerwe and Erixon, 2023), which involves leveraging base technologies like the IoT, cloud computing, or big data (Frank et al., 2019), as well as other more complex technologies

Table 1
Glossary of topics and concepts.

Topic/Concept	Definition	Author (s)
Intelligence	*"… the ability of a system to act appropriately in an uncertain environment, where appropriate action is that which increases the probability of success, and success is the achievement of behavioral subgoals that support the system's ultimate goal."*	Albus (1991, p. 474)
Artificial Intelligence	*"… the ability of a system to identify, interpret, make inferences, and learn from data to achieve predetermined organizational and societal goals."*	Mikalef and Gupta (2021, p. 3)
Smart Manufacturing	*"… the integration of cyber-physical systems, IoT, cloud computing, service-oriented computing, AI and data science"*	Kusiak (2018, p. 509)
Servitization	*"… the strategic business transformation from the traditional "pure" product-centered offering to an integrated product and service value offering"* through three main aspects*: "service offering, which involves a focus on developing the servitization strategy; resource base, determining the required conditions; and activity system, outlining the activities to be performed."*	Ayala et al. (2019, pp. 43, 47)
Service Platform	*"… a modular structure that comprises tangible and intangible components (resources) and facilitates the interaction of actors and resources (or resource bundles)."*	Lusch and Nambisan (2015, p. 166)
Service System	*"… an open system (1) capable of improving the state of another system through sharing or applying its resources … and (2) capable of improving its own state by acquiring external resources"*	Maglio et al. (2009, p. 403)
Service Ecosystem	*"… a relatively self-contained, self-adjusting system of resource-integrating actors connected by shared institutional arrangements and mutual value creation through service exchange."*	Vargo and Lusch (2016, p. 10)
Ecosystem Value Capture	Mechanism that aligns relationships within and between service systems through efficiency, accountability, shared customer value and novelty, and supports resource integration, value co-creation and governance interactions.	Chen et al. (2021); Frost et al. (2019)

Source: Authors own creation

such as AI-enabled smart manufacturing, to enhance service value generation within their ecosystems. The concept of value system encompasses systems spanning from raw material suppliers to end customers (Porter and Millar, 1985), while ecosystems can operate within value systems, adopting market or networked organizational forms (Kohtamäki et al., 2019). The dynamics of ecosystem evolution concerning SDL have been articulated in various contexts. Servitization encourages collaborative efforts aimed at jointly discovering, creating and capturing value within ecosystems (Kolagar et al., 2022; Lindhult et al., 2018). This approach is rooted in an interactive business logic in value-creating systems, which facilitates the emergence of novel value constellations among complementary actors engaged in co-innovation in product-service networks (Jovanovic et al., 2022). This interactive business logic is empowered by information gathered via supporting AI-enabled smart manufacturing virtual interfaces that link actors, activities and resources effectively to form efficient and effective value constellations (Kolagar et al., 2022; Porter and Millar, 1985). Under SDL, servitization plays a facilitative role in the co-creation process (Parry et al., 2012). When combined with suitable technologies such as base and AI-enabled smart manufacturing, it can positively impact manufacturing competitiveness in terms of value creation and capture (Lusch, 2011; Porter and Heppelmann, 2014; Vargo and Akaka, 2012)

AI-enabled smart manufacturing consists of a combination of technologies encompassing smart digital platforms, smart products and capabilities, and smart manufacturing technologies. Regarding smart digital platforms, there are several perspectives (de Reuver et al., 2018). One defines them as purely technical artifacts, with the platform being an expandable codebase, and the ecosystem consisting of third-party modules that complement the codebase (Tiwana and Konsynski, 2010). Alternatively, a digital platform can also be seen as a socio-technical system encompassing software and hardware components along with organizational processes and standards (Kapoor et al., 2021). Digital platforms offer standardized design principles and a digital framework, enabling interactions among diverse users who might not engage otherwise. The platform's intricately designed structure, including flexible and set fees, influences user participation and ultimately affects the net benefits users derive from potential interactions (Broekhuizen et al., 2021). Smart products have the ability to independently learn, predict and take action. They encompass both the hardware setup of a responsive product and advanced AI software. These software capabilities enable the product to connect with broader networks, respond to environmental shifts, analyze patterns, engage in reasoning and learn, essentially encapsulating intelligence (Raff et al., 2020). The capability of independent reasoning and decision-making is fundamental when defining a product's intelligence (Porter and Heppelmann, 2014).

The National Institute of Standards and Technology (NIST) defines smart manufacturing as a system of integrated collaboration in manufacturing that dynamically responds to evolving demands across factory settings, supply networks and customer requirements (Kusiak, 2018). In a similar vein to the principles governing smart digital platforms and smart products and capabilities, smart manufacturing relies heavily on harnessing data utilization capacities to strengthen a company's position within its operational ecosystem (Tao and Qi, 2017). This framework facilitates the acquisition of data and streamlines decision-making processes throughout the business value chain. Considering the distinctive role of digital platforms in generating and seizing value in the digital economy (Gawer, 2022), the strategic exploitation of data by firms via smart products to leverage synergies between products and platforms, thereby enhancing the performance of ecosystems and capturing value for themselves and their partners (Stonig et al., 2022), and the foundational significance of smart manufacturing in elucidating a firm's profit generation and economic gains via value capture (Favoretto et al., 2021), it is posited that:

H2. AI-enabled smart manufacturing positively relates to ecosystem value capture.

3.3. The mediating role of servitization

AI-enabled smart manufacturing is a crucial factor in driving sophisticated service-oriented business models (Bustinza et al., 2022; Cimini et al., 2018). Shifting toward services not only enables organizations to extract more value from their digital technologies but also outperforms the benefits derived from product-centric models (Abou-foul et al., 2021; Davies et al., 2023). In this context, servitization, as defined by Baines et al. (2017), requires manufacturing firms to create and capture value by offering services instead of relying solely on the upfront sales of physical products. Subsequent studies have highlighted the convergence of digital technologies and servitization to explain how value is captured. Kohtamäki et al. (2020) looked at the impact of this relationship on business performance, suggesting that the influence of digital technologies on business performance is linked to servitization. They argue that servitization empowers organizations that have digitalized their operational processes and infrastructure in order to make use of the capabilities offered by digital technologies and their potential economic value. Furthermore, Abou-foul et al. (2021) explored the interconnectedness between digital technologies, servitization and financial performance, revealing that servitization acts as a mediator in this relationship. Similarly, other researchers, such as Davies et al. (2023) and Yang et al. (2023), arrived at parallel conclusions, suggesting that servitization plays a partial mediating role in the relationship between digital technologies and the financial performance of firms, a mediation route referred to as the customization pathway by Vendrell-Herrero et al. (2024).

This study adopts the SDL perspective to explore the role of AI-enabled smart manufacturing in service ecosystems. SDL posits that value is co-created through the integration of resources by various actors (Lusch, 2011; Vargo and Lusch, 2017). This collaborative process unfolds within complex networks, characterized by time, replication, and institutionalization (Chandler and Vargo, 2011). Service ecosystems emerge as loosely coupled networks where value propositions are exchanged and co-created (Lusch, 2011). AI-enabled smart manufacturing offers significant potential for both value co-creation and capture. By enhancing cost-effectiveness (Frank et al., 2019) and enabling the creation of smart digital platforms, manufacturers can expand revenue streams and foster enduring customer relationships through continuous interactions (Garcia Martin et al., 2019). This aligns with the SDL emphasis on value co-creation and the role of ecosystems in facilitating such interactions. To better understand the interplay between AI-enabled smart manufacturing and servitization within service ecosystems, it is crucial to distinguish between service platforms and service systems (Frost et al., 2019). Service platforms, as modular structures facilitating interactions, enable resource integration (Lusch and Nambisan, 2015). Conversely, service systems provide the environment for value co-creation and governance (Frost et al., 2019). AI-enabled smart manufacturing is a critical resource within this dynamic environment, as it enhances value propositions by enabling adaptation to changing conditions (Khan et al., 2024). Moreover, it operates at the intersection of individual efforts and broader social structures, emphasizing the importance of balancing micro- and macro-level perspectives (Chandler and Vargo, 2011). By understanding the interplay between these elements, we can gain valuable insights into how AI-enabled smart manufacturing contributes to value co-creation and ecosystem evolution.

On the convergence between new technologies and service systems, authors such as Bustinza et al. (2022) have revealed the positive synergy between smart manufacturing and servitization. Smart manufacturing serves as a strategic tool for companies to elevate entry barriers, thereby reinforcing their position and enabling value capture in the supply chain network (Ziaee Bigdeli et al., 2017). However, by assuming such a position, companies must invest in aligning their internal business model portfolio with the external environment by focusing on the development of service-based business models (Rabetino et al., 2018). In this context, smart products aim to facilitate automated, flexible and efficient production management, along with the creation of new data-driven services (Mittal et al., 2018). Similarly, smart digital platforms facilitate value capture in various ways, such as reducing costs, increasing revenues, or capturing new revenue streams from services (Madanaguli et al., 2023). In short, previous studies indicate that, individually, smart digital platforms, smart products and capabilities, and smart manufacturing interact with servitization as a means to achieve higher value. Based on the above, the following hypothesis is put forward:

H3. Servitization mediates the relationship between AI-enabled smart manufacturing and ecosystem value capture.

3.4. Industrial sector context

To comprehend the interconnectedness between technologies, service business models and ecosystems, it is imperative to acknowledge the diversities inherent in industrial sectors (Kohtamäki et al., 2022). Several classifications exist for digital-intensive industrial sectors, as identified by studies such as the McKinsey Global Institute (2015) or Calvino et al. (2018). These classifications rely on a set of indicators that gauge whether a particular sector exhibits relatively high or low degrees in specific dimensions. These dimensions usually encompass the intensity of investment in digital technologies, intermediate consumption of technological products, utilization of robotics and the presence of specialists in digital technologies. According to these categorizations, digitally-intensive industries encompass sectors where AI-enabled smart manufacturing is extensively integrated throughout the production cycle (Porter and Heppelmann, 2014, 2015). This incorporation involves the use of intelligent machinery for production processes and the creation of smart end products. Examples of such sectors include electronics and automotive manufacturing, where intelligent machines are deployed to craft intelligent products. Conversely, digitally-augmented industries comprise sectors where AI-enabled smart manufacturing primarily enhances the input aspect of production (Porter and Heppelmann, 2014, 2015). Even though these sectors use intelligent machinery and processes, the resulting products offered to consumers may not inherently possess digital intelligence. Industries falling into this category, such as food processing and clothing manufacturing, benefit from intelligent machines by enhancing production efficiency without necessarily yielding smart end products for consumers. According to Porter and Heppelmann (2015), the transformation induced by digital technologies extends beyond manufacturing, and resonates in service industries. For instance, airlines equipped with smart planes and connected on-board systems can significantly enhance operational efficiency by diagnosing maintenance issues mid-flight and arranging for immediate remedies upon landing. This improvement in service operations does not necessarily impact consumer experience (the product) in itself. Considering that the intersectional effect between technologies, service business models and ecosystems is sector-specific (Bustinza et al., 2019; Kohtamäki et al., 2022), the following hypothesis is put forward:

H4. Industrial context moderates the mediating role of servitization in the relationship between AI-enabled smart manufacturing and value capture ecosystems.

Fig. 1 illustrates the relationship between AI-enabled smart manufacturing supported by Industry 4.0 foundational (base) technologies, servitization, industry sectors, and value capture within the ecosystem.

4. Data and method

This section presents a comprehensive overview of the database and variables used in the study, aiming to provide a clear context for the subsequent analysis. The selection criteria and sampling process ensure a representative dataset, with no significant differences observed between sub-samples. The study categorizes companies into digitally-intensive and digitally-augmented industries to facilitate hypothesis testing. Measures were taken to address non-response bias (NRB) and common method bias (CMB), ensuring the reliability and validity of the data. By analyzing these variables using Smart-PLS, the study aims to uncover relationships between AI-enabled smart manufacturing and value capture within service ecosystems. The introduction of these constructs sets the stage for a detailed exploration of their interactions and implications in the manufacturing sector.

4.1. Database

A sample comprising 303 survey responses was collected using Qualtrics in 2022. 30 responses were initially obtained for a pilot study aimed at assessing questionnaire reliability, followed by collection of the remaining responses. Focus was centered on manufacturing companies in the UK and Germany, resulting in a dataset consisting of 149 German-based companies and 154 with headquarters in the UK (see Table 2). This research did not reveal any statistically significant differences between the sub-samples. Country selection was based on their recognized

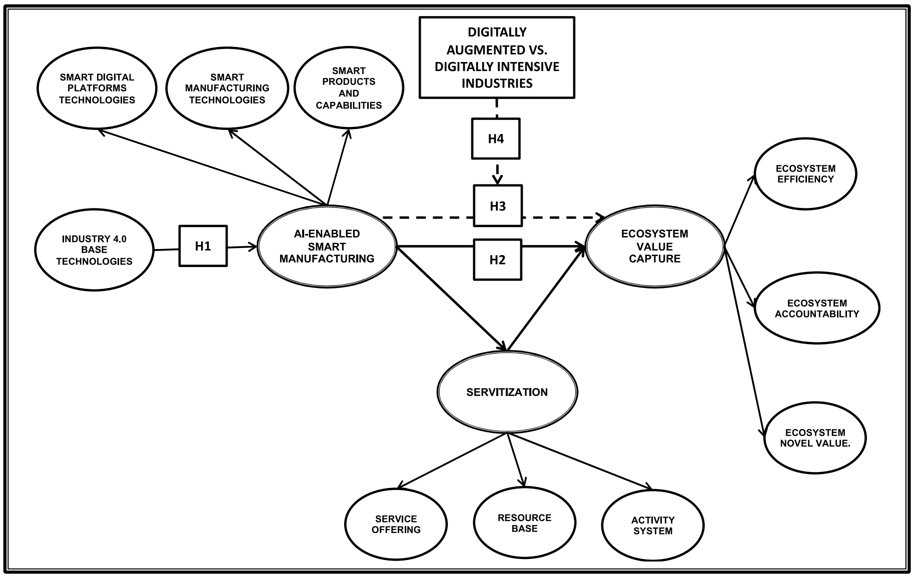

Fig. 1. Conceptual model and hypotheses presented.
Source: Authors own creation

Table 2
Profile of sampled firms considering industry composition.

		Full Sample	Processing-based NAICS-31	Science-based NAICS-32	Machinery-based NAICS-333/336	Computer-based NAICS 334/335
			Food, beverage and textile	Printing, chemical, pharmaceutical	Vehicles, machines, turbines	Hardware and electronics
	Observations	303	58	45	55	145
SURVEY DATA	Country: UK	154	28	24	28	74
	Country: Germany	149	30	21	27	71
	Firm age average	29.84	32.50	35.24	33.95	25.43
	Firm size					
	100 < … < 499	103	19	19	14	51
	500 < … < 999	70	10	11	17	32
	1000 < … < 4999	81	16	10	18	37
	5000 < … < 9999	24	8	1	6	9
	Over 10,000	25	5	4	0	16
	IT investment (%)[a]	31.59	23.42%	29.99%	32.03%	35%
	Total assets (Av.)	1,397,230	2.062500	628,566	2,888,367	2,345,340
	Patents (Av.)	31.18	21.30	21.89	69.73	463.31
	t-TEST	Observations	Base Technologies	AI-Enabled Smart Manufacturing	Servitization	Value Ecosystem
	UK	154	0.115	0.059	0.157	0.023
	Germany	149	−0.119	−0.061	−0.162	−0.023
	P-value		0.22	0.50	0.08	0.80

P-value is obtained from a *t*-test considering |difference|>0.
[a] This is the ratio with annual revenues.
Source: Authors own creation

leadership in implementing technological advancements and their substantial manufacturing sectors (Davies et al., 2023). Moreover, the UK and Germany are notably positioned among nations that perceive digital transformation as a strategic opportunity to enhance governmental capacity for innovation, flexibility and adaptation within evolving contexts (Hammerschmid et al., 2024). Specifically targeting the manufacturing sector, firms with Standard Industrial Classification (SIC) codes ranging from 31 to 33 and a workforce of over 100 employees were the central focus. The resulting population meeting these criteria totals 17,183 manufacturers. Considering the population parameters—95% confidence level, 5% margin of error and $p = 0.15$ − a minimum sample size of $n = 222$ was calculated, ensuring sample representativeness (Vendrell-Herrero et al., 2023). To facilitate hypothesis testing, the sample was divided into digitally-intensive Industries ($n = 103$) and digitally-augmented industries ($n = 203$). This intentional division ensures a balanced representation of both industry types for testing hypothesis H4.

To address non-response bias (NRB), an assessment using a *t*-test was conducted that compared early and late respondents across all variables included in analysis. The results revealed no statistically significant differences. Regarding potential common method bias (CMB), concern arises when a single method measures various variables. A standard procedure involves loading all items onto a single factor via exploratory factor analysis. In this dataset, five factors emerged, with the first factor explaining only 19.4% of variance. Consequently, CMB does not appear to be a significant issue in this research.

4.2. Variables and measurement model

The independent variable, *Industry 4.0 Base Technologies*, was assessed using the indicators proposed by Frank et al. (2019): IoT (e.g., integration of sensors and computing in an Internet environment via wireless communication …), cloud computing (e.g., on-demand network access to a shared pool of computing resources …), big data (e.g., data collection from systems and objects …), and analytics (e.g., data mining and machine learning …). By construction, it is an "emerging variable", since the implementation of base technologies is formed by the sum of these technologies and so, on the contrary, they are not the consequence.

Regarding the dependent variables, the AI-enabled smart manufacturing scale was adapted from Frank et al. (2019) and Vendrell-Herrero et al. (2021), which incorporates three dimensions to form a second-order construct: smart digital platforms, smart products and capabilities, and smart manufacturing technologies. AI-enabled smart manufacturing is an "emerging variable" for the same reason as Industry 4.0 base technologies. Furthermore, the servitization scale (Ayala et al., 2019; Davies et al., 2023) is a consolidated Likert-based measurement instrument consisting of three dimensions: service offerings that manufacturers adopt as part of their service innovations; the resource base required for servitization; and the activity system, which is the set of activities required to operationalize servitization. This variable is anticipated to mediate the relationship between AI-enabled smart manufacturing and ecosystem value capture. Amit and Zott (2015) and Fehrer et al. (2018) emphasized the need to balance value co-creation and value capture in service ecosystems by internalizing the positive externalities generated by each actor's value proposition. These ecosystems, described as self-regulating systems (Vargo and Lusch, 2017), generate value through evolving and intensifying relationships among actors. A critical aspect of value capture in these ecosystems is harnessing positive network externalities, which involve benefits that arise from interactions among multiple actors (Amit and Zott, 2015). Katz and Shapiro (1985) distinguished between direct network effects, where the value of a service increases with the number of users, and indirect network effects, which result from the widespread adoption of a standard. Technologies are operant resources on the SDL −those capable of acting on other resources to create value. In our model, AI-enabled smart manufacturing is viewed as an essential operant resource for value co-creation. The synergistic relationship between AI-enabled smart manufacturing's value propositions and servitization produces both direct and indirect network effects, thereby boosting the service ecosystem's overall economic viability and achieving systemic value capture. (Chen et al., 2021) suggested that value capture in such ecosystems can be measured through efficiency, accountability, shared customer value, and innovation. Therefore, we used the *Ecosystem value capture* variable, comprising three dimensions—ecosystem efficiency, ecosystem accountability and ecosystem novel customer value—, validated for the first time, and draws from Chen et al. (2021). A five-point Likert scale is used for all dependent variables (ranging from 1 for "strongly disagree" to 5 for "strongly agree").

In order to assess the measurement model's validity and consistency, several analyses were conducted using Smart-PLS (Hair et al., 2011). This methodology was chosen as it is particularly suitable when there are latent and emergent variables in a model (Henseler et al., 2015). Table 3 shows the various indicators' factor loadings. In all cases, these factor loadings remain within acceptable levels, with only a few falling slightly below 0.7, and are significant at 5%. Nonetheless, it was deemed appropriate to retain them in order to maximize the measurement model's content validity. In the case of emerging constructs, the VIF is

Table 3
Scale and construct analysis.

Items	Scale				
	Pa	AVE	VIF	Weight	Loadings
Industry 4.0 Base Technologies (composite)					
Internet of Things			1.62	0.36***	0.80***
Cloud Computing			1.57	0.41***	0.78***
Big Data			1.68	0.21***	0.80***
Analytics			1.62	0.27***	0.79***
AI-enabled Smart Manufacturing (composite)					
Smart Digital Platform Technologies			2.61		
Digital Platforms with supplier				0.45***	0.81***
Digital Platforms with customers				0.42***	0.81***
Digital Platforms with other company units				0.37***	0.72***
Smart Manufacturing Technologies (composite)			2.15		
Vertical integration			1.15	0.40***	0.72***
Virtualization			1.54	0.36***	0.74***
Automation			1.42	0.13*	0.69***
Traceability			1.44	0.18**	0.70***
Flexibility			1.54	0.18*	0.73***
Energy management			1.55	0.13*	0.74***
Smart Products and Capabilities			2.78		
Product monitoring				0.37***	0.81***
Product control				0.33***	0.77***
Product optimization				0.32***	0.77***
Product autonomy				0.28***	0.72***
Servitization	0.91	0.08			
Service Offering					
Strategic aspect for competitiveness				0.40***	0.77***
Compete in service differentiation				0.35***	0.75***
Delivered spontaneously if customer need is identified				0.32***	0.69***
More customer-oriented than competitors				0.30***	0.69***
Resource Base					
Develop new competencies for service				0.36***	0.71***
Human capital as a competitive source				0.31***	0.74***
Internal knowledge as a competitive source				0.34***	0.76***
Flexible to market changes, quickly adapt				0.34***	0.75***
Activity System					
Service and product jointly developed				0.30***	0.75***
Service integrated in strategic decision on product and solution				0.30***	0.74***
Functional areas work together to develop new products				0.24***	0.70***
Customer involvement in developing new products and services				0.25***	0.69***
Other business areas involved in product and service development				0.29***	0.72***
Ecosystem Value Capture	0.85	0.68			
Ecosystem Efficiency					
Mechanism for integrating customer needs				0.64***	0.87***
Mechanism for seamlessly integrating design and service				0.54***	0.82***
Ecosystem Accountability					
Mechanisms for sharing data to reduce incompatibility				0.58***	0.84***
Mechanisms for assisting partner in quality improvements				0.60***	0.84***
Ecosystem Novel Customer Value					
Mechanisms for opportunity identification				0.38***	0.77***
Mechanisms for new solution simulation				0.41***	0.84***
Mechanisms for new customer-oriented development				0.45***	0.81***

Note: t-values in parentheses. Significance level.; $p < 0.001$; $p < 0.01$; $p < 0.05$.
Source: Authors own creation

used to analyze multicollinearity. In all cases, the values are within reference values (Benitez et al., 2020). Second-level variables were subsequently constructed for AI-enabled smart manufacturing, servitization and ecosystem value capture, each comprising three sub-dimensions. Reliability of the construct score ($\rho_A > 0.7$) (Dijkstra and Henseler, 2015), convergent validity (Average Variance Extracted >0.5) and discriminant validity (Table 4) was confirmed using the Fornell-Lacker Criterion and HTMT ratio (Henseler et al., 2015). In all instances, the indicators fall within values considered acceptable. Consequently, it can be asserted that this measurement model is valid for investigating the relationships established in the theoretical model.

5. Results

Smart-PLS and Adanco were used to conduct the analysis, which encompassed both the entire sample and the subgroups comprising firms from digitally-augmented and digitally-intensive industries. This approach aimed to investigate distinctions between these two industry types. Table 5 presents the results of the structural equations for the full sample and the results for each subgroup of firms from digitally-augmented and digitally-intensive industries. To check the model fits the data, SRMR and d_{ULS} indicators were used. In both cases they were found to be lower than their hypothesis contrasts, so are therefore theoretical models that fit the empirical data (Benitez et al., 2020). Table 6 shows the total, indirect and partial effects in the two subgroups, and the Welch-Satterhwait test results to check the hypothesis that both estimates are significantly different between the two samples.

Hypothesis 1 argues that Industry 4.0 base technologies have a positive impact on AI-enabled smart manufacturing. The validity of this hypothesis is supported by the results presented. Table 4 therefore shows that Industry 4.0 base technologies have a positive and significant effect on AI-enabled smart manufacturing in the two industry types considered ($\beta = 0.754$, $p < 0.001$). Equally significant is the relationship for both digitally-intensive industries ($\beta = 0.784$, $p < 0.001$) and digitally-augmented industries ($\beta = 0.737$, $p < 0.001$). According to the Welch-Satterhwait difference test shown in Table 5, no differences were observed ($\Delta\beta = 0.047$, n.s.). It can therefore be affirmed that the effect is significant and does not vary between the two industry types.

Hypothesis 2 argues that AI-enabled smart manufacturing relates positively to ecosystem value capture. First, according to the data for the full sample, the effect of AI-enabled smart manufacturing on ecosystem value capture is positive and significant ($\beta = 0.357$, $p < 0.001$). When an analysis differentiating between industry types was performed, it was seen that the direct effect is not significant in the case of digitally-intensive industries ($\beta = 0.158$, n.s.), however, in digitally-augmented industries the direct effect is significant ($\beta = 0.446$, $p < 0.001$). Furthermore, if the total effect is considered, i.e., both directly and through servitization, AI-enabled smart manufacturing is significant in both cases and shows no significant difference with regard to its impact ($\beta_{DII} = 0.587$, $p < 0.001$; $\beta_{DAI} = 0.754$, $p < 0.001$; $\Delta\beta = -0.078$, n.s.). Therefore, taking these results as a whole, it can be confirmed that the results support hypothesis 2.

To test hypothesis 3, which argues that servitization mediates the relationship between AI-enabled smart manufacturing and ecosystem value capture, and hypothesis 4, arguing that the mediation of servitization in the relationship between AI-enabled smart manufacturing and ecosystem value capture depends on industrial sector context, both analyses were combined. On the one hand, as previously stated, in the case of digitally-intensive industries, the direct relationship between AI-enabled smart manufacturing and ecosystem value capture is not significant ($\beta = 0.158$, n.s.). On the other hand, the indirect effect through servitization is significant ($\beta = 0.429$, $p < 0.001$), as is the total effect ($\beta = 0.587$, $p < 0.001$). The VAF indicator (Nitzl et al., 2016) was also calculated (VAF = 73.08%). With this data, servitization can be considered to mediate the relationship totally between AI-enabled smart manufacturing and ecosystem value capture in the case of digitally-intensive industries.

In digitally-augmented industries, the direct relationship between AI-enabled smart manufacturing and ecosystem value capture is significant ($\beta = 0.446$, $p < 0.001$), as is the indirect effect through servitization ($\beta = 0.219$, $p < 0.001$) and total effect ($\beta = 0.665$, $p < 0.001$). Considering this data together with the VAF indicator (VAF = 32.93%), it can be concluded that mediation is partial in this case. Hence, in both industry types, servitization mediates the relationship between AI-enabled smart manufacturing and ecosystem value capture, and therefore supports hypothesis 3. Moreover, the relevance and intensity of mediation depends on the industry type, so the type of mediation and relationship between AI-enabled smart manufacturing and ecosystem value capture is contingent on the industry type, as stated in hypothesis 4.

Finally, the difference in servitization strategy relevance between the two industry types should be highlighted. In both digitally-intensive ($\beta = 0.663$, $p < 0.001$) and digitally-augmented industries ($\beta = 0.399$, $p < 0.001$), the direct effect of servitization on value capture is positive and significant. However, the direct effect of servitization is greater ($\Delta\beta = 0.264$, $p < 0.05$) in the case of digitally-intensive industries. This result suggests that companies in these industries have more incentive to adopt servitization since its impact on value capture is more significant than in digitally-augmented industries. Considering this greater relevance of servitization and the fact that it serves as a mediator between AI-enabled smart manufacturing and value capture within the ecosystem, it can be concluded that this strategy is especially significant in the context of digitally-intensive industries.

Table 4
Measurement model. Discriminant validity.

	Fornell-Lacker Criterion			
	Base I4.0	AI-Enabled Smart Manufacturing	Servitization	Ecosystem Value Capture
Base_I4.0	1.00			
AI-Enabled Smart Manufacturing	0.564	0.913		
Servitization	0.599	0.686	0.861	
Ecosystem Value Capture	0.753	0.579	0.635	0.887
	Heterotrait-Monotrait Ratio HTMT			
	Base I4.0	AI-Enabled Smart Manufacturing	Servitization	Ecosystem Value Capture
Base_I4.0				
AI-Enabled Smart Manufacturing	0.594			
Servitization	0.658	0.795		
Ecosystem Value Capture	0.809	0.653	0.750	

Source: Authors own creation

6. Discussion

The concept of servitization has evolved from a mere conceptualization of product-service value-added offerings aimed at securing increased revenue streams to the perspective of a growing services ecosystem facilitated by continually advancing technology (Vandermerwe and Erixon, 2023). The domain of servitization has evolved in tandem with the different phases of supply chain evolution by increasing value in the supply chain by means of a network conceptualization (Potter et al., 2015; Ziaee Bigdeli et al., 2017). This evolution manifests itself as digital servitization, which supports supply chains via platforms (Kapoor et al., 2021; Madanaguli et al., 2023) and nurtures

Table 5
Structural model: Reliability of structural equations.

	Total Sample			Digitally-Intensive Industries			Digitally-Augmented Industries		
	Dependent variables			Dependent variables			Dependent variables		
	AI-Enabled Smart Manufacturing	Servitization	Ecosystem Value Capture	AI-Enabled Smart Manufacturing	Servitization	Ecosystem Value Capture	AI-Enabled Smart Manufacturing	Servitization	Ecosystem Value Capture
Base Technologies	0.754*** (24.091)			0.784*** (20.458)			0.737*** (17.075)		
AI-Enabled Smart Manufacturing		0.579*** (11.072)	0.357*** (5.305)		0.645*** (7.834)	0.158 n. s (1.574)		0.544*** (8.671)	0.446*** (5.601)
Servitization			0.481*** (6.995)			0.663*** (9.493)			0.399*** (4.549)
Reliability (adjusted-R^2)	0.333	0.567	0.533						
SRMR	0.0259 (HI99 = 0.0263)								
d_{ULS}	0.0369 (HI99 = 0.0381)								

Note: t-values in parentheses. Significance level ***p < 0.001; **p < 0.01; *p < 0.05.
Source: Authors own creation

Table 6
Direct, indirect and total effect. Mediation of servitization in the AI-enabled smart manufacturing and ecosystem value capture relationship.

	Digitally-Intensive Industries	Digitally-Augmented Industries	Welch-Satterthwait Difference Test
Direct effect			
Base Technologies - > AI-enabled smart manufacturing	0.784 (20.458)***	0.737 (17.075)***	0.047 (0.783) n. s.
AI-enabled smart manufacturing - > Ecosystem value capture	0.158 (1.574) n.s.	0.446 (5.601)***	−0.288 (2.141)*
AI-enabled smart manufacturing - > Servitization	0.645 (7.834)***	0.544 (8.671)***	0.101 (1.135) n. s.
Servitization - > Ecosystem value capture	0.663 (9.493)***	0.399 (4.549)***	0.264(2.150)*
Indirect effect			
AI-enabled smart manufacturing - > Ecosystem value capture	0.429 (5.281)***	0.219 (3.455)***	0.21 (2.092)*
Total effect			
AI-enabled smart manufacturing - > Ecosystem value capture	0.587 (8.019)***	0.665 (14.445)***	−0.078 (0.861) n.s.
Mediation Intensity (VAF)	73.08%	32.93%	

Note: t-values in parentheses. Significance level ***p < 0.001; **p < 0.01; *p < 0.05.
Source: Authors own creation

service ecosystems (Lusch, 2011). These phases have been propelled by the rise of technological innovations such as Industry 4.0 (Lafuente et al., 2023; Wamba and Queiroz, 2022), AI (Chien et al., 2020; Mikalef and Gupta, 2021) and smart manufacturing (Bustinza et al., 2022; Kusiak, 2018), which have contributed to the development of these service ecosystems. The present study advances the current understanding by proposing a new framework where servitization and AI-enabled smart manufacturing converge to help firms capture value. Servitization, the shift to offering services, allows manufacturers to remain essential if their products continue to be central to develop value propositions (Burström et al., 2021). AI-enabled smart manufacturing, which incorporates technologies like IoT, cloud computing, big data, and analytics, improves product quality, flexibility, and customization (Mittal et al., 2018). These technologies synchronize production with suppliers (Wamba and Queiroz, 2022), promote collaborative manufacturing (Lafuente et al., 2023), and enable manufacturers to focus on core competencies while leveraging shared capabilities for innovation (Frank et al., 2019; Ziaee Bigdeli et al., 2017). In this framework, AI is crucial in evolving smart digital platforms (Gawer, 2022; Kapoor et al., 2021; Madanaguli et al., 2023), smart products and capabilities (Porter and Heppelmann, 2014, 2015; Vendrell-Herrero et al., 2021), and smart manufacturing technologies (Bustinza et al., 2019; Cimini et al., 2018; Kusiak, 2018). The interaction between servitization and AI-enabled smart manufacturing enhances product development and supplementary services within smart manufacturing, expanding their value proposition and capture (Chen et al., 2021).

7. Theoretical and managerial implications

7.1. Theoretical implications

This study's findings have several implications with regard to the academic literature on servitization, Industry 4.0 (e.g., AI) and service ecosystems (Bustinza et al., 2022; Chien et al., 2020; Culot et al., 2020; Vargo and Akaka, 2012). First, it provides empirical insights into the role of servitization in the optimal configurational arrangement between digitalization, value propositions development, and ecosystem outcomes. In this respect, the study suggests that servitization mediates the relationship between AI-enabled smart manufacturing and ecosystem value capture, complementing the results obtained by previous studies −e.g., see Davies et al. (2023); Harrmann et al. (2023); Schulz et al. (2023), and supporting the role of servitization as an enabler of customization (Vendrell-Herrero et al., 2024). This emphasizes the importance of services in fostering a harmonious relational context that encourages seamless integration and interaction between actors and resources, which ultimately leads to co-creation (Fang, 2019). This result supports the SDL premise, which suggests that digital technologies (AI-enabled smart manufacturing) along with servitization are operant resources capable of effectively increasing value co-creation opportunities and processes in varying spatial and temporal settings within service value ecosystems (Chandra and Rahman, 2024; Vargo and Akaka, 2012).

Second, this study depicts the specific contexts where servitization plays a crucial mediating role. This insight is critical in order to understand how value is captured within ecosystems; this argument can be summarized as follows: AI-enabled smart manufacturing technologies exhibit different applications in digitally-augmented and digitally-intensive industries (Calvino et al., 2018; McKinsey Global Institute, 2015). In di gitally-augmented industries, these technologies primarily bolster existing systems by means of services and platforms, and place emphasis on operational efficiency (Wamba and Queiroz, 2022). Conversely, in digitally-intensive industries, servitization has the potential to fundamentally reshape business models, enabling personalized and large-scale interactions with customers capabilities previously unattainable (Kolagar et al., 2022). Services wield greater importance in digitally-intensive industries, but their differentiating impact diminishes in the realm of digitally-augmented industries. Moreover, digitally-intensive industrial environments may foster more favorable conditions for ecosystem implementation due to the existence of a clearly segmented customer base, facilitating smoother integration (Burström et al., 2021). Services can thereby stimulate the emergence of ecosystems, which often evolve more organically owing to their proximity to customers (Kohtamäki et al., 2022). In essence, digitally-intensive industries undergo more substantial shifts in business models compared to their digitally-augmented counterparts.

Finally, in line with the SDL view of operant resources, a key contribution made by this study lies in the convergence of servitization with digital technologies (Abou-foul et al., 2021; Davies et al., 2023) in order to enhance performance outcomes. In this respect, this study empirically elucidates the following: First, it considers an array of digital base technologies that sustain smart production, which include the IoT, cloud computing, big data, and analytics. Second, focus is on a particular measure of artificial intelligence in manufacturing—the concept of AI-enabled smart manufacturing systems. This underscores the importance of considering the layers of technological implementation used to harness the full potential of AI and digital technologies (Frank et al., 2019; Shi et al., 2023). Finally, this study differs from prior research in that it explores the digitalization ➜ servitization ➜ performance pathway by focusing on a more nuanced outcome variable. In so doing, emphasis is placed on the significance of identifying the roots of competitive advantage beyond merely assessing the financial benefits derived from the simultaneous implementation of AI-enhanced production systems and service-augmented business models. Moreover, it is argued here that value co-creation for the entire ecosystem is paramount, as it elevates actors to a be central in developing value propositions. These insights align with earlier studies elucidating the role of AI and digital technologies within service ecosystems (Akaka and Vargo, 2014; Cimini et al., 2018; Gawer, 2022; Kohtamäki et al., 2022). Overall, by highlighting the critical mediating role of servitization, the results support Lusch's (2011) argument to reframe the entire supply chain domain within a service ecosystem framework.

7.2. Managerial implications

This study has significant managerial implications. First, it upholds the full implementation of foundational technologies before adopting an AI-enabled smart manufacturing strategy (Shi et al., 2023). Second, it suggests that firms should focus their AI-enabled smart manufacturing efforts on developing service-based business models as the pathway to capturing value in digitally-intensive industries. In addition, this study stresses that in order to understand the intricate relationship between technologies, service-based business models and ecosystems, acknowledgement of the inherent diversities in industrial sectors is required in turn (Kohtamäki et al., 2022). In this regard, the results suggest that digitally-intensive industries integrate AI-enabled smart manufacturing extensively into their production cycles, using intelligent machinery for production processes and creating smart end products, as seen in electronics and automotive manufacturing. Conversely, digitally-augmented industries enhance production efficiency using intelligent machinery but may not inherently generate smart end products for customers as seen in food processing and clothing manufacturing. Consequently, AI-enabled smart manufacturing strategy in digitally-augmented industries should prioritize mechanisms to incorporate customer needs, assist partners in quality improvements, identify opportunities, and stimulate new solutions, more so than focus on complex service business models.

7.3. Limitations and future research avenues

Limitations are inherent in the quantitative research method used, particularly in surveys that primarily collect structured data, thereby constraining the depth of information gathered. Moreover, this method is time-limited, which restricts the analysis of variable evolution over specific periods. To address these constraints, future research should contemplate carrying out longitudinal analysis or mixed-method approaches. Future studies could also explore the time intervals between foundational (base) technologies, AI-enabled smart manufacturing implementation, and the development of service business models, as this may be of use to determine possible configurational arrangements. Similarly, investigating the breadth and depth of servitization could provide valuable insights in order to understand the technological nuances. Finally, future research avenues could look into the impact of various technological innovations, such as digital service innovation (Opazo-Basáez et al., 2022) or treble innovations (Vendrell-Herrero et al., 2023) on service ecosystems.

8. Conclusions

The concept of servitization has evolved significantly in accordance with the competitive landscape, shifting from a mere product-service value addition strategy to playing a central role in new service ecosystems driven by technological operant resources such as Industry 4.0 and AI. This study advances the understanding of servitization by exploring its convergence with AI-enabled smart manufacturing, demonstrating how these elements together facilitate value capture within service ecosystems. The integration of servitization and AI-enabled technologies, like IoT, cloud computing, big data, and analytics, enhances product quality, flexibility, and customization, fostering collaborative manufacturing and allowing firms to leverage shared capabilities for developing value propositions. The findings highlight that servitization mediates the relationship between AI-enabled smart manufacturing and ecosystem value capture, supporting the SDL framework. This mediation underscores the importance of services in creating a context for cocreation, as digital technologies and servitization act as operant resources increasing value creation opportunities. The study's theoretical contributions lie in empirically validating these relationships and depicting the specific contexts where servitization plays a critical role, particularly in digitally-intensive and digitally-augmented industries. This differentiation emphasizes the need to tailor AI-enabled smart manufacturing strategies to the industry's digital intensity. From a managerial perspective, the study suggests that firms should fully implement foundational technologies before adopting AI-enabled smart manufacturing strategies. In digitally-intensive industries, the focus should be on developing service-based business models to capture value, while digitally-augmented industries should prioritize customer needs, partner quality improvements, and innovative solutions. These insights provide a nuanced understanding of the interplay between digitalization, servitization, and value capture, emphasizing the importance of cocreating value for the entire ecosystem.

CRediT authorship contribution statement

Oscar F. Bustinza: Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Luis M. Molina:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ferran Vendrell-Herrero:** Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Methodology, Investigation, Funding

acquisition, Formal analysis, Data curation, Conceptualization. **Marco Opazo-Basaez:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Data availability

The data that has been used is confidential.

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