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Digital service innovation for smarter production: Servitized-AI progress towards smart products

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ABSTRACT

This paper investigates if the simultaneous integration of servitization and AI-intensive strategies lead manufacturers to develop products with more advanced analytically 'smart' capabilities. The proliferation of smart products, equipped with sensors and connectivity, has significantly enhanced value creation through remote monitoring, control, optimization, and autonomy. While the potential of digital technologies from these products is well-recognized, true smart capabilities require more than mere data collection; they necessitate AI-augmented Digital Service Innovation (DSI). This study posits that integrating AI with digital servitization enables manufacturers to develop advanced smart products. Utilizing a unique dataset from 576 Spanish manufacturing firms for 2023, the study employs an ordered probit model with sample selection to assess the impact of servitization and AI-intensive strategies on smart product development. Findings reveal that while both servitization and AI-intensive strategies contribute to the development of analytically smarter products, only the combined implementation significantly advances a product's smart capabilities. This research underscores the critical role of DSI in the progression of smart products through monitoring, control, optimization, and autonomy stages.

1. Introduction

Sensors, connectivity, analytical software, and algorithmic virtues are increasingly being added to products to augment their value creation potential and enhance their remote monitoring, control, optimization, as well as autonomy capabilities (Bustinza et al., 2024; Rabetino et al., 2024). These product enhancements are transforming products into so-called smart products (Porter and Heppelmann, 2014; 2015; Rijsdijk and Hultink, 2009). Much emphasis has been placed on the big data generated by such smart products, as well as on the scalable customization capacity that such product-based intelligence can offer to manufacturers (Berente et al., 2021; Raff et al., 2020; Vendrell-Herrero et al., 2021). However, in order to be able to reach such benefits and be 'smart', products need more than just sensors and data collection abilities (Opazo Basáez et al., 2024; Rabetino et al., 2024). To advance up the smart product capability scale and offer true autonomy-enabled smart products, manufacturers are likely to require AI-augmented servitization, termed as Digital Service Innovation (DSI) (Opazo Basáez et al., 2022; Rabetino et al., 2024; Raff et al., 2020; Schulz et al., 2023).

DSI involves transforming the development and delivery of servitization-augmented products by harnessing digital technologies (Rabetino et al., 2024). Servitization and servitization-intensive strategies consist of service-centric business models where producers bundle products together with services to deliver higher value to customers (Bustinza et al., 2018). DSI redefines servitization and traditional service models by integrating to them large-language based or generative AI tools and platforms (an AI-intensive strategy) to create enhanced or entirely new service experiences, reshaping how value is designed, provided, and accessed in the digital era (Narvaiza et al., 2023; Opazo Basáez et al., 2024). As such, a configurative view of technology following the principals of the structurational model (Orlikowski, 1992) is adopted where AI is not just a technology and servitization not just a production technique, but they are both part of a wider strategic value generation system that can be at the core of the idiosyncratic capabilities that give a product its 'smart' character. There is a gap, however, in the literature as to whether manufacturers can potentially offer products that develop much 'smarter' capabilities by combining the analytical capacity of AI to the service-based business logic of servitization (Kohtamäki et al., 2022; Vaillant et al., 2025).

For instance, the company Kone has incorporated sensors into its

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elevators (Ayala et al., 2025a). But it is only by using artificial intelligence to analyse the collected data that their elevators truly developed the remote condition monitoring and optimization service capabilities that warrant the ‘smart’ adjective (Qvist-Sørensen, 2020). In the MedTech industry, companies such as Medtronic are developing AI-powered medical devices that are transforming healthcare by enhancing real-time personalized diagnostics, treatment, and patient monitoring. These devices, such as intelligent pacemakers, smart insulin pumps, and surgical tools, leverage machine learning algorithms to analyse data, predict potential health issues, and personalize treatment plans, ultimately leading to improved patient outcomes and more efficient healthcare delivery (Kelly, 2024; Medtronic, 2025; Rowland et al., 2024). Similarly, Tesla utilizes AI and machine learning techniques to anticipate maintenance issues, enabling their vehicles to self-notify its owners about the need for maintenance or even to self-diagnose and remediate identified problems autonomously (Ayala et al., 2025a; Tredinnick, 2017). Such smart products rely heavily on DSI, where servitization, which provides the value logic and relational infrastructure, meets with the cognitive and autonomous capacity of artificial intelligence to generate the capabilities that make them ‘smart’ (Bustinza et al., 2022; Opazo Basáez et al., 2024; Paschou et al., 2020; Rabetino et al., 2024).

Servitization can strategically utilize digital and AI (AI-intensive strategy) to redefine service design, delivery, and customization, leading to innovative offerings, operational enhancements, and increased value creation (Opazo Basáez et al., 2024). Through AI-intensive strategies, servitization becomes the skills and knowhow that are required to cultivate ‘smart capabilities’ that connected-devices and sensor-augmented products can potentially generate (Kohtamäki et al., 2021; Vaillant and Lafuente, 2024).

The standard framework for the ‘smart capabilities’ of products presents a nested structure depending on the product's degree of analytic capabilities. This classification progresses through a sequence of monitoring, control, optimization, and autonomous capabilities (Bohnsack et al., 2024; Porter and Heppelmann, 2014; Vendrell-Herrero et al., 2021). The analysis proposed in this paper therefore aims to understand the role of DSI on the smart capabilities of products in order to answer the study's research question: Are manufacturers that implement servitization and utilize AI-intensive strategies more likely to have products with advanced analytical capabilities in terms of progression across monitoring, control, optimization and autonomous nested abilities?

To do so a unique dataset was collected using a survey specifically designed for this research which encompasses a sample of 576 Spanish manufacturing firms for 2023. The core results of the full model estimated via ordered probit model with sample selection indicate that the implementation of servitization and AI-intensive strategies by manufacturers do contribute to the development of products with more advanced analytically smart abilities, in terms of their progression towards fully autonomous smart products. However, this positive association is found when servitization and AI-intensive strategies are jointly implemented by manufacturers, consistent with a DSI approach. For manufacturers implementing either servitization or AI-intensive strategies on their own, the adoptions of these strategies were not found to play a positive role on the progression of the manufacturers’ products towards more advanced analytically smart capabilities.

The results of the study presented in this paper offer new theoretical postulates that help adjust the current body of knowledge in business management to some of the changes brought on by the advent of ever more technologically enhanced products leading manufacturers towards smart solution delivery (Huikkola et al., 2022a; Rabetino et al., 2024). Similarly, the paper's findings add to the practical guidelines that can contribute to practitioners' understanding of these transformative changes and facilitate better managerial response and alignment. The paper contributes a new perspective to the Digital Service Innovation framework by bringing in the role of service-intensive as well as AI-intensive strategies in inducing more advanced and autonomous smart products.

The study answers the calls for greater research on the specificities of the capacity-generating potential of AI-augmented servitization (Ayala et al., 2025a, 2025b; Bustinza et al., 2024; Kohtamäki et al., 2025; Lafuente and Sallan, 2024). The study does so by also bringing in the separate, though highly overlapping, smart product literature (Berente et al., 2021, 2021; Raff et al., 2020; Rijsdijk and Hultink, 2009; Vendrell-Herrero et al., 2021). The study innovates by introducing the importance of the technification of products as an output measure. The result of the study not only supports the nested smart product capabilities scale originally introduced by Porter and Heppelmann (2014), but demonstrates the importance of the mutual adoption of service-intensive and AI-driven strategies by manufacturers to facilitate their development of smarter products in terms of their products’ progression up this scale towards fully autonomous smart products.

2. Theoretical background and hypotheses development

This study focuses on digital service innovation (DSI) not digital servitization. Although closely connected, DSI and digital servitization reflect distinct dimensions of a firm's shift toward a digitally driven, service-oriented business model. Digital servitization refers to the strategic transition from product-centric offerings to integrated product-service systems, enabled by digital technologies that enhance customer value and operational efficiency (Kohtamäki et al., 2019). In contrast, DSI focuses specifically on the creation and advancement of new digital services—typically built on technologies such as AI, cloud computing, and the Internet of Things (IoT)—that deliver novel forms of customer value (Opazo Basáez et al., 2022; Rabetino et al., 2024). DSI more specifically focuses on the value-enhancing service-based ‘smart’ innovations that this study conceptually models and empirically tests. Despite the study's focus on DSI in accordance with its objective to analyse the production of increasingly smarter products, much of the theoretical foundation from the digital servitization literature does help to articulate the conceptual argument that leads to the model proposed in this study (Kowalkowski et al., 2024). It should be understood, nevertheless, that the objective is not to analyse the strategic transition towards product-service systems, but rather the narrower analysis of strategy that contributes towards the production of products with smarter features and capabilities (Marić et al., 2024; Monroy-Osorio, 2024; Rabetino et al., 2024).

Building on Orlikowski's (1992) structurational model, which frames technology in organisations as both a shaping force and a product of strategic decisions and human agency, the DSI perspective positions technology as something organisations actively configure rather than merely adopt. Under this view, AI is more than a technical tool and servitization more than a method of production; together, they form components of a broader strategic system for generating novel value. This system helps establish the distinctive capabilities that make a product ‘smart.’ Manufacturers that skillfully align their technological choices and service delivery with the value-creation logic of their products can achieve unique value propositions, foster service innovation, and reshape or renew their systems (Akaka and Vargo, 2014; Mekalef, 2023). For smart products, this alignment translates into advancing their analytical capabilities toward autonomously enhancing value.

2.1. Smart product capabilities

An increasing number of products are being equipped with sensors and connectivity features that enhance their ability to create value by enabling remote adaptability, responsiveness, multifunctionality, autonomous operations, and humanlike interaction. These advancements are transforming traditional products into what are known as “smart products” (Bohnsack et al., 2024; Porter and Heppelmann, 2014, 2015; Rijsdijk and Hultink, 2009). What such products can achieve has been described as an entirely new set of functions and capabilities, which can be grouped into four areas: monitoring, control, optimization, and autonomy (Porter and Heppelmann, 2014). Each capability is nested and sets the stage for the next level, where manufacturers must choose the set of capabilities to give their products so as to deliver its customers maximum value, and in so doing define its competitive positioning.

The smart capability that a product integrates—monitoring, control, optimization, and autonomy—will enhance its functionality and value (Porter and Heppelmann, 2014). By leveraging sensors and external data sources, these products can continuously **monitor** their condition, performance, and environment, enabling real-time alerts, usage insights, and improved product design, market segmentation, and service strategies. **Control** features go beyond monitoring by adding bidirectional interaction that allows remote operation and personalization of performance through embedded or cloud-based software, enabling unprecedented levels of customization. To this, **optimization** uses analytics and historical data processed using algorithms to enhance efficiency, perform predictive maintenance, and minimize downtime, often eliminating the need for physical interventions. Combining these features, **autonomy** allows products to operate independently, adapt to user preferences, learn from their environment, and self-diagnose service needs, reducing human intervention, improving safety in hazardous conditions, and enabling functionality in remote settings (Porter and Heppelmann, 2014; Vendrell-Herrero et al., 2021). These integrated capabilities redefine traditional product roles, offering significant advancements in operational efficiency and user experience.

As such, products integrating smart capabilities can potentially offer more differentiated customer-oriented value than that generated from the simple physical object at its core (Vaillant et al., 2025a,b; Vendrell-Herrero et al., 2021). The servitized and service-augmented smart capabilities of these products enable solution-based and customized value generation (Opazo et al., 2023).

2.2. Servitization and smart products

Servitization occurs when manufacturers shift from selling standalone products to offering integrated solutions that combine products with value-added services (Cusumano et al., 2015; Rabetino et al., 2024; Vandermerwe and Rada, 1988). In servitization, products are bundled with services to deliver higher value to customers. This transition from product-centric to service-centric business models encourages manufacturers to develop "smart" products equipped with autonomous capabilities, such as real-time data monitoring and adaptive features, to better meet customer needs and enable seamless service delivery (Bustinza et al., 2022; Vargo and Lusch, 2004).

Such a service-oriented logic emphasises value co-creation through heightened customer interaction and infaces (Karpen et al., 2012; Vargo et al., 2017). This service-intensive value logic requires a relational infrastructure favouring continuous customer interaction and strong service feedback loops (Raff et al., 2020; Sjödin et al., 2020). Servitization therefore incentivizes manufacturers to invest in smart, connected products (e.g., IoT-enabled devices) as strategic resources. By embedding service-oriented capabilities leading to optimization and autonomy into products, manufacturers improve their ability to deliver advanced services, such as predictive maintenance, remote diagnostics, and adaptive system upgrades (Favoretto et al., 2022; Gebauer et al., 2021; Opazo-Basaez et al., 2023). The basis of digital servitization suggest that developing smarter autonomous products allows firms to deliver solution-based value that dynamically meets customer demands for advanced services while maintaining operational flexibility and scale (Kohtamäki et al., 2022; Paschou et al., 2020; Vaillant et al., 2025a,b).

As a result, servitization and the manufacturing of smarter products are interlinked through their shared emphasis on leveraging digital technologies, fostering co-created value, and adapting to dynamic market and customer needs (Vendrell-Herrero et al., 2021, 2025). When servitization is linked to smart, connected products, it "*enable a fundamental shift from reactive service to preventive, proactive, and remote service*" that form the basis of optimizing autonomous efficacy (Porter and Heppelmann, 2015: 11). Smart (er) products can deliver autonomous product operations that self-coordinate with other products and systems, self-customise, self-diagnose, and self-optimize, all of which are associated with digital servitization and advanced value generating service delivery (Kohtamäki et al., 2022, 2025). Therefore, the 'smarts' of a product potentially comes from service-augmentation attained through its connected capabilities. Not only does servitization optimize the value generation of products when they have smart capabilities, but combining the real-time connectivity, data collection, and analytics of smart products with servitization opens advanced monetization opportunities and the capacity for new revenue schemes, such-as subscriptions, pay-per-use, or pay-per-performance to be realized (Lafuente et al., 2023a,b).

Furthermore, servitization positions manufacturers as part of service-driven value ecosystem, where the demand for smart, autonomous products emerges from the need to provide seamless, value-added services (Adner, 2006; Kohtamäki et al., 2019). Autonomous capabilities enable products to function as active participants within these ecosystems, driving the co-evolution of services and technologies as an operant resource capable of providing further capabilities to create value (Akaka and Vargo, 2014). Empirical studies support these theoretical arguments by demonstrating that servitization encourages manufacturers to invest in connected and autonomous technologies (Kowalkowski et al., 2015; Baines et al., 2009, 2013). For example, manufacturers implementing predictive maintenance services often develop smart, IoT-enabled products capable of autonomous performance monitoring, control, and optimization (Porter and Heppelmann, 2014).

Based on the above arguments, we deduce the following hypothesis:

H1. *The adoption of servitization plays a significant positive role on the production of smarter products (in terms of their progression towards fully autonomous smart products).*

2.3. AI and smart products

In the realm of manufacturing, AI can be instrumental in enabling smarter autonomous products. Data collection is insufficient by itself. Digitalized products also require AI to analyse and interpret the accumulated data and be able to take better decisions as a result. Manufacturers adopting AI-intensive strategies amplify their data-driven sensing abilities, their decision-making, as well as their operational reconfiguration capacity, all of which are essential for creating "smart" products (Bohnsack et al., 2024). AI-intensive product strategies use AI software, tools, or platforms to enhance the customizable functionality of products. Technologies like machine learning and predictive analytics empower manufacturers to design products with features such as prognostic maintenance, autonomous navigation, and adaptive performance (Kohtamäki et al., 2021; Lee, 2023). What distinguishes AI from previous decision-making technologies is its real-time information management, planning, and implementation capacity that when integrated strategically can help firms to develop new smart algorithm evolution capabilities (Mikalef et al., 2023). These advancements allow products to operate independently, learn from user interactions, and adapt to changing environmental conditions, fostering resilience in complex and uncertain contexts (Escribá-Carda et al., 2024; Nasiri et al., 2020; Vaillant et al., 2024).

Techniques like reinforcement learning allow products to make autonomous decisions, while supervised learning models improve the effectiveness in smart product use through enhanced quality control capacity with real-time defect detection capabilities and predictive quality assurance (Krakowski et al., 2023). Such AI-enabled traits allow the production of highly customized products that incorporate autonomous functionality. In line with the premises of the sociotechnical systems theory (Walker, 2015), AI-intensive strategies create a bridge between human expertise and advanced technologies, driving the development of smarter, autonomous products. By integrating artificial intelligence, manufacturers can automate repetitive processes while allowing human workers to focus on higher-order tasks, thereby enhancing product intelligence and adaptability (Raisch and Fomina, 2024). AI provides a strategic resource, enabling firms to collect, process, and analyse vast amounts of data in real time. This capability enhances manufacturers' ability to design adaptive products that embed autonomous features such as self-monitoring, optimization, and decision-making into their offerings (Teece, 2018).

Beyond production, AI-driven strategies enhance collaboration across ecosystems by fostering innovation among manufacturers, technology providers, and users (Lafuente and Sallan, 2024). This ecosystem-wide integration leads to the creation of products that seamlessly operate within connected systems (Cusumano et al., 2024). Additionally, AI's capacity for continuous learning through data processing and pattern recognition enables adaptive improvements in both manufacturing processes and product performance over time (Davenport and Kirby, 2016; Lee, 2023). Ultimately, these strategies contribute to smarter, autonomous products capable of navigating and thriving in dynamic environments.

From these arguments, the following hypothesis is formulated:

H2. *The adoption of AI-intensive strategy plays a significant positive role on the production of smarter products (in terms of their progression towards fully autonomous smart products).*

2.4. Digital service innovation and smart products

As argued above, servitization and AI-intensive strategies are important ingredients associated with the production of smarter products in terms of their analytically advanced capabilities. However, rather than functioning as standalone or opposing approaches, the theoretical principles of Digital Service Innovation (DSI) suggest that both are essential and must work in tandem to stimulate the development of intelligent, autonomous products (Rabetino et al., 2024). Without servitization, AI remains a technological add-on; without AI, servitization lacks real-time intelligence to scale and be truly autonomous (Kohtamäki et al., 2019; Naeem et al., 2024; Opazo Basáez et al., 2022).

Rooted in key studies on servitization (Vandermerwe and Rada, 1988), technological innovation (Christensen, 2015), and digitalization (Rai et al., 2006), DSI has emerged as a transformative theoretical framework for enhancing industrial competitiveness and value creation in dynamic business ecosystems (Opazo Basáez et al., 2022). DSI represents an innovative model of service delivery where services and their technological underpinnings are integrated into a cohesive and adaptable system that evolves to meet user and business needs (Narvaiza et al., 2023).

By leveraging servitization, AI, and advanced data analytics, DSI principals suggest that firms ought to design dynamic service solutions while continuously reconfiguring business models to meet shifting customer expectations (Huikkola et al., 2022a, 2022b; Rabetino et al., 2024). This transitions manufacturing firms from offering standalone products to delivering digital service solutions that are highly customizable and autonomous (Kohtamäki et al., 2020; Naik et al., 2020). Whereas servitization provides value logic and relational infrastructure, AI and digital capabilities enable cognitive and autonomous capacity. Their joint implementation is seen from a DSI perspective to transform products from static artifacts into self-learning, autonomous service systems capable of sensing, reasoning, and acting (Ayala et al., 2025b; Kohtamäki et al., 2025). This paradigm allows for the creation of products capable of delivering personalized, data-driven value propositions, supported by digitally enhanced services and customer relationships (Kowalkowski et al., 2015; Tronvoll et al., 2020).

Bustinza et al. (2024) empirically analysed the symbiotic convergence of AI and servitization within smart products, whilst Jia et al. (2024) found that the joint implementation of an AI-augmented digital servitization was required in order to unlock the full value of a product's digitally collected data. The benefits of the simultaneous and coordinated implementation of AI within product-service systems can therefore unleash both back-office productive processes as well as client-oriented front-office analytical capabilities that contribute towards the production of analytically smarter products capable of more autonomous value creation (Ayala et al., 2025b; Kohtamäki et al., 2025).

Through the convergence of servitization and AI, DSI empowers manufacturers to embed intelligence into products, enabling real-time data collection and analysis (Burton et al., 2024), remote monitoring, optimization, and autonomous functionality across complex and dynamic contexts (Beverungen et al., 2021; Porter and Heppelmann, 2015). The servitization-AI synergies of DSI foster innovation by aligning AI-driven insights with service-oriented strategies, enabling firms to design smarter products that adapt dynamically to user needs and operational environments. From this reasoning, it is suggested that:

H3. *The joint implementation of servitization and AI-intensive strategies by manufacturers significantly contribute to their production of smarter products (in terms of their progression towards fully autonomous smart products).*

Fig. 1 presents the study's conceptual model, illustrating the hypothesized relationships between servitization, AI-intensive strategy, and the production of smarter products.

3. Data and method

3.1. Data

In this study, the firm is the unit of analysis, and the target population includes manufacturing businesses. The data used to test the proposed hypotheses was obtained from two sources of information. First, accounting and organizational data for the selected businesses was collected from the Spanish database SABI (Sistema de Análisis de Balances Ibéricos). From this database, it was possible to identify an initial sample of 9413 small (number of employees >10), medium, and large-sized manufacturing firms (NACE codes: 10–31).

In a second stage, we applied a questionnaire specifically designed for the purpose of this research. Details on the instrument are provided in section 3.2. The survey instrument was pre-tested with two scholars and one industry expert to ensure the clarity of questions, and the targeted respondents were limited to executives and top management familiar with their firm's strategic and technological operations. The survey was conducted by a professional market investigation and public opinion service firm that was directly monitored by the researchers. The data was collected via structured interviews in which respondents were asked to answer closed-ended questions (both dichotomous and Likert-based). The data was collected between June and September 2023. Targeting executives and top managers ensured that responses reflected informed perspectives on firms' strategic and technological practices, which are central to our analysis. Also, these informants are particularly relevant because of their direct involvement in technology adoption and product-service strategy making processes.

We received a total of 626 responses and, after removing observations with missing data (incomplete surveys = 44 cases, and firms with no employment data for the survey year = 6 cases), the final sample included information on 576 manufacturing firms, which represents an effective response rate of 6.12 %. The sample is representative of the targeted population of firms: with a 95 % confidence level the sampling margin error is 3.96 %, which falls within acceptable levels in quantitative studies (Juslin et al., 2007).

The geographic diversity and profile differences further corroborate the validity of the final sample. The sampled firms are spread across Spain's autonomous communities (Catalonia = 16.32 %, Valencia = 12.63 %, Andalusia = 11.93 %, Madrid = 9.47 %, Galicia = 7.72 %,

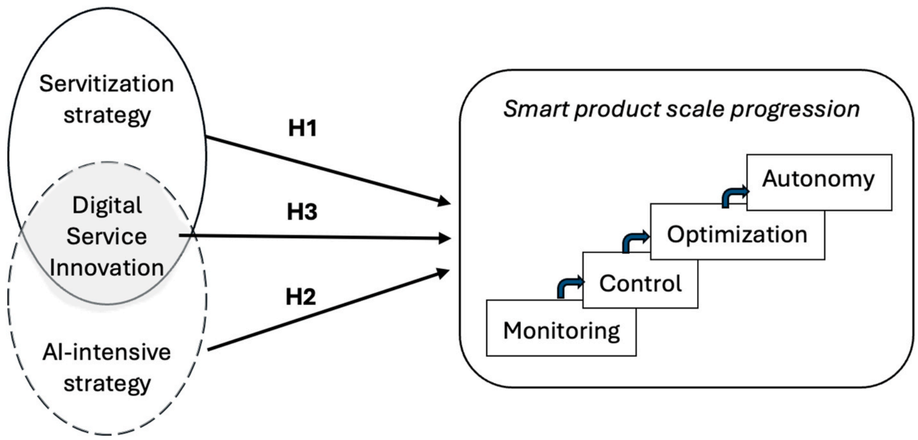

Fig. 1. Conceptual model.

Murcia = 7.54 %, Castile-La-Mancha = 7.37 %, Basque Country = 6.84 %, Castile Leon = 5.26 %, Aragon = 3.86 %, Navarra = 3.51 %, Asturias = 1.75 %, Extremadura = 1.40 %, La Rioja = 1.40 %, Canary Islands = 1.23 %, Balearic Islands = 1.05 %, and Cantabria = 0.70 %). In addition, average firm size—in terms of number of employees—is 34.90 (range = 21–411 workers), while the sampled firms report an average of 30.30 years of market experience (range = 2–89 years). Concerning firms' industrial activity, figures for the industry breakdown presented in Table 1 verify the diversity of the economic activity of the firms included in the sample.

3.2. Variable definition

Dependent variable.—Following Porter and Heppelmann (2014, 2015), the survey instrument included specific questions to measure the level of 'smartness' of the connected products offered by the sampled firms. Specifically, managers were asked to indicate the capabilities of their connected products, distinguishing between four progressively advanced categories: A) 'monitoring' (i.e., use of sensors and external data sources), B) 'control' (i.e., software embedded in the product for enhanced bidirectional product functionality), C) 'optimization' (i.e., use of algorithms to optimize product performance and allow predictive diagnostics and service), and D) 'autonomy' (i.e., fully autonomous, smart products that self-coordinate with other products and systems to generate tailor-made improvements and self-diagnostic tasks). From Fig. 2 it can be observed that among firms with digitalized, connected products (N = 278), 21.70 % report the use of tracking sensors ('monitoring' stage), whereas 12.67 % use specific software in order to better control the functions of their products ('control' stage). In addition, 8.34 % of these firms have introduced algorithms that optimize product operations and performance, in terms of identification of diagnostic and customization possibilities ('optimization' stage); and 6.60 % reported that their products are fully autonomous and smart as a result of the combination of 'monitoring', 'control', and 'optimization'

Table 1
Industry distribution of the sampled firms.

Industry	NACE codes	Number of cases	Proportion of total
Food processing	10–12	154	26.74 %
Textile	13	23	3.99 %
Chemicals	20–21	39	6.77 %
Plastic	22–23	60	10.42 %
Metal	24–25	117	20.31 %
Electronic and machinery	26–28	82	14.24 %
Furniture	31	19	3.30 %
Other	14-18, 29	82	14.24 %
Total		**576**	**100.00 %**

capabilities ('autonomy' stage). These categories represent a hierarchical progression across the smart product development scale, where each capability builds on the preceding one. Therefore, the dependent variable used in this study is treated as ordered, reflecting the nested and cumulative nature of specific investments and technological capabilities of firms' products (Vendrell-Herrero et al., 2021).

Servitization.—Similar to prior work (e.g., Bustinza et al., 2024; Lafuente et al., 2023a,b), respondents were directly asked two sequential questions regarding the nature of their firm's offering. Concretely, managers first identified whether the firm solely sells product-centric goods, while the second question captured whether value-adding complementary services are also integrated into the firm's offering. By combining these two questions we were able to generate a binary variable identifying firms that have adopted a servitization strategy (Kohtamäki et al., 2021). Descriptive results in Table 2 show that 67 % of firms with digitalized products provide combined product-service offerings (32.34 % for the full sample) so; therefore, they fall into the servitized category.

AI-intensive strategy.—Managers were questioned as to the implementation of AI tools and platforms as part of their strategic orientation (Opazo-Basáez et al., 2022; Vendrell-Herrero et al., 2021). Beyond more common standalone AI applications, specific questions were included in the survey instrument to identify those firms that use more comprehensive AI platforms ("Does your business use artificial intelligence (AI) platforms [such as Cassandra, Cloudera, DataStax, Databricks, AWS IoT, Hadoop, SAS, Watson (IBM), Azure (Microsoft), TensorFlow, Google AI Platform, or similar]?"). In addition to detecting the presence of AI technologies in firm's processes, a second question captured the functional application of such technologies. Specifically, managers were asked to indicate whether AI technologies were integrated into one or various stages of the firm's solution-delivery process (problem identification, solution development, and solution implementation) (Huikkola et al., 2022a; Lafuente and Sallan, 2024; Rabetino et al., 2024). Together, these two questions allowed us to identify firms in which AI technologies represent concrete, operationally functional investments rather than perceptions or intentions. Based on the combined responses, we constructed a dummy variable identifying firms that have fully integrated AI tools or platforms in their operations, reflecting the specific use of these technologies to complement human capabilities and improve human-controlled decision making. From the descriptive statistics presented in Tables 2 and it can be seen that among the sub-sampled of firms with digitalized products (N = 278) 41 % have adopted an AI-intensive strategy, whereas this figure stands at 19.79 % for the full sample of firms with and without digitalized products.

Offer integratedness.—An integrated offer enhances manufacturers' ability to consistently deliver value over time, enabling the provision of integrated solutions to their customers (Huikkola et al., 2022b; Lafuente

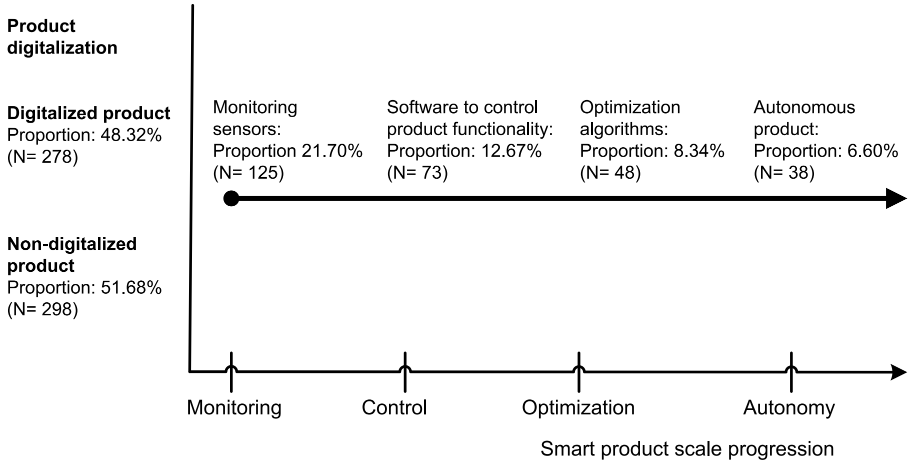

Fig. 2. Smart product scale progression (sample size = 576 firms)
For each stage of the smart product scale progression, proportions refer to the full sample.
Source: Authors' elaboration.

Table 2
Descriptive statistics and bivariate correlations for the sub-sample of firms with digitalized products (N = 278 firms).

Variable	Mean	Std. dev.	1	2	3	4	5	6	7	8
1. Monitoring sensors	0.39	0.49	1.00							
2. Control software	0.23	0.42	0.68***	1.00						
3. Optimization algorithms	0.14	0.35	0.50***	0.74***	1.00					
4. Autonomous product	0.13	0.34	0.48***	0.72***	0.96***	1.00				
5. Firm size (employees)	35.30	19.62	−0.02	0.02	−0.05	−0.05	1.00			
6. Firm age (years)	30.43	15.60	0.09*	0.09*	0.05	0.04	0.10*	1.00		
7. Servitization	0.67	0.47	−0.10*	−0.02	0.03	0.02	0.00	0.02	1.00	
8. AI-intensive strategy	0.41	0.49	0.07	0.12**	0.13**	0.12**	0.02	0.03	−0.07	1.00
9. Offer integratedness	0.07	0.53	0.11**	0.14**	0.15***	0.16***	0.06	−0.10*	0.03	0.07

Sample size: 278 firms with digitalized products. *, **, *** indicate that bivariate correlations are significant at the 10 %, 5 %, and 1 %, respectively.

and Sallan, 2024). Therefore, a greater integratedness of products enables manufacturers to become performance providers, actively involved in the customer's technical operations. This process might be especially relevant for firms with digitalized products (Krakowski et al., 2023). The analysis of the electro-technical industry by Matthyssens and Vandenbempt (2008) is a good example of the strategic connection between offer integratedness and product digitalization. The authors found that these firms can alleviate rent loses by offering customized solutions integrating business processes and technical applications in security systems. This process can be enhanced by digital technologies to produce data from motion detection sensors in security systems and analyse such data to generate predictive intrusion detection models that improve security notification alerts.

Four items based on a 7-point Likert scale (1 = totally disagree, 7 = totally agree) were used to operationalize offer integratedness. These items reflect the degree to which the firm's offering includes interdependent elements of products and complimentary services (‘Does the firm's offering primarily include interdependent elements of products, services, systems and knowledge?‘), how the firm's offering influence customer's operations and performance (‘Your clients’ technical operations are influenced by your offer’ and ‘Yours clients’ performance is influenced by your offer’), and the extent to which the connection between the firm and its customers is necessary to generate more effective solutions (‘Developing your offer requires deep knowledge of the customer's industrial processes'). A confirmatory factor model (CFA) was performed to verify that the instrument's questions correctly measure the offer integratedness construct. The outcome of the CFA indicates that the four items load into a single factor (all standardized factor loadings are greater than 0.50), and the reliability of these items to measure offer integratedness is corroborated by diagnostic statistics: Cronbach's alpha test of reliability (0.76), KMO test of sampling adequacy (0.64), and the Bartlett test of sphericity (369.55, p-value <0.001). The validity of these items to measure offer integratedness is further corroborated by the results of the CFA analysis: composite reliability = 0.76, and average variance extracted (AVE) = 0.47, RMSEA = 0.093, and SRMR = 0.038.

Control variables.—We control for firm size, age, industry, and location in all model specifications. Business size is measured by the number of employees, while business age is expressed in years. In all specifications the variables firm size and age were logged to reduce skewness. We included a set of industry dummies (food processing is the omitted category) as well as a set of regional dummy variables linked to Spain's Autonomous Communities (Andalusia is the reference territory) in order to rule out potential industry- and territorial-specific effects that might affect firms' smart product strategy.

3.3. Test of non-response bias, early response bias and common method bias

We examined the potential presence of bias in the study data. To assess non-response bias, we compared the 44 firms excluded from the final sample (due to incomplete surveys) with the 576 firms included in the final sample across several dimensions: firm size (employment), firm age (years), servitization, the adoption of an AI-intensive strategy, offer integratedness, presence of digitalized product, and the four categories of the smart product scale (monitoring, control, optimization, and automation). The results of the Mann-Whitney *U* test, reported in Table A1 of the Appendix, indicate that firms included in the final sample make slightly greater use of more monitoring sensors (23 %) compared to those excluded from the sample (11 %) (Mann-Whitney *U* test = 1.79, p-value = 0.07). Similarly, sampled firms report a marginally higher proportion of autonomous products (9 %) relative to the group of excluded firms (7 %) (Mann-Whitney U test = 1.80, p-value = 0.07). On contrary, no significant differences were observed for the rest of variables. These results suggest that non-response bias does not affect the validity of the study's findings.

Following the temporal separation approach (Podsakoff et al., 2012), we used the non-parametric Mann-Whitney U test to evaluate whether the distribution of responses by early (first 10 % of the sample) and late (last 10 %) respondents are drawn from the same sample, that is, whether the two response vectors share the same underlying distribution. This procedure was applied to the same set of variables analysed in the non-response bias test described above. As reported in Table A1 (Appendix), of the 10 analysed variables, significant differences in response distribution were only found in two cases: firm size, where early respondents are larger firms (Mann-Whitney U test = 4.25, p-value <0.001), and firm age where early respondents are firms with slightly greater market experience (Mann-Whitney U test = 1.81, p-value = 0.06). Therefore, the comparisons between early and late respondents corroborate that the distribution of the main variables does not raise early-response bias concerns.

Finally, we conducted the Harman's single-factor test to evaluate the potential presence of common method bias (Podsakoff et al., 2003; Fuller et al., 2016). Under this procedure, evidence of common method bias arises when a factor model that includes all variables produces a single factor that accounts for more than 50 % of the total variance in the measurement items (Fuller et al., 2016). To enhance the robustness of the analysis, we estimated two exploratory factor models: model A which includes the 10 variables examined in the preceding bias tests (firm size, firm age, servitization, the adoption of an AI-intensive strategy, offer integratedness, presence of digitalized product, and the four categories of the smart product scale), and model B which replaced the four smart product categories with the main ordered dependent variable used in this study, which captures the hierarchical progression along the smart product development scale. For factor model A, the analysis produced three factors with eigenvalues >1, and the first factor with the highest eigenvalue accounts for 34.02 % of the total variance. For factor model B, three factors with eigenvalues >1 were extracted, with the first factor accounting for 25.90 % of the total variance. In both models, the proportion of variance explained by the first factor falls well below the 50 % threshold, which corroborates that common method bias is not a concern in this study.

3.4. Method

Following the theoretical arguments presented in this study, developed upon the premises of the Digital Service Innovation conceptual framework (Kowalkowski et al., 2013; Opazo Basáez et al., 2022; 2024; Tronvoll et al., 2020), firms are likely to adopt smart-product strategies based on expected competitive improvements resulting from the digitalization of their products (Mikalef et al., 2023; Rojas-Segura et al., 2023). Nevertheless, without first modelling the decision to digitalize products, any model explaining the effect of servitization or AI-intensive strategies on the development of smart products would produce biased results, regardless of whether the model controls for covariates linked to the development of smart products (Wooldridge, 2010).

Firms can choose to digitalize their products and, inter alia, we argue that this process is driven by the strategic decision of developing a more integrated offer. In addition, only firms whose products are digitalized have the capacity to generate smart capabilities and progress across the smart product scale. In this case, the sample is censored, and this gives rise to a sample-selection problem (Heckman, 1990).

In addition, similar to other economic problems based on the study of discrete multinomial-choice variables (e.g., trade-to-trade stock price changes, injury severity of car crashes, or crop diversification) (Hausman et al., 1992; Piedra-Bonilla et al., 2020; Savolainen et al., 2011), engagement in the different stages leading to the development of smart products implies an inherently ordered decision-making process.

Standard regression models are not viable to test the study's hypotheses, and an analysis that addresses both potential sample selection and the evaluation of ordered AI-intensive strategies offers a more comprehensive modelling approach.

Heckman (1979) characterizes the sample selection problem as a special case of the omitted variable problem in which the inverse Mills ratio (λ) is the omitted variable in an outcome equation to be estimated. Therefore, in this study the two-step Heckman model with an ordered outcome equation (De Luca and Perotti, 2011) was chosen as econometric tool to estimate consistent coefficients for the effects of servitization and AI-intensive strategies on the different stages of the smart product scale progression.

The full model estimated via ordered probit model with sample selection has the following form:

$$\text{Digital product}_i = \delta_0 + \delta_1 \text{Offer integratedness}_i + \sum \delta_k \text{Controls}_i + \gamma_i \tag{1}$$

$$\begin{aligned} \text{Smart product scale progression}_i &= \beta_0 + \beta_1 \text{Servitization}_i \\ &+ \beta_2 \text{AI} - \text{intensive strategy}_i + \beta_{12} \text{Servitization}_i \\ &\times \text{AI} - \text{intensive strategy}_i + \beta_3 \lambda_i + \sum \beta_k \text{Controls}_i + \varepsilon_i \end{aligned} \tag{2}$$

In the first step of the Heckman's model (equation (1)), a probit model in which the dependent variable equals to one for firms with digitalized products, is used to estimate the inverse Mills ratio. In this equation, $\boldsymbol{\delta}_j$ is the vector of coefficients, and ‘offer integratedness’ is the instrument variable used to model the firms' endogenous decision to digitalize their products. The second step (equation (2)) estimates the outcome equation via an ordered probit model with the inverse Mills ratio (λ) as an explanatory variable. In equation (2), ‘Servitization’ and ‘AI-intensive strategy’ are the key independent variables to explain the different stages of the smart product scale progression, while $\boldsymbol{\beta}_j$ is the vector of parameter estimates for the ordered models.

In both equations, ‘Controls’ is the vector of control variables accounting for the potential effects of firm size (ln employees), firm age (ln years of market experience), location (set of regional dummies), and industry (set of industry dummies). Finally, the terms ε and γ are the error terms of the probit (selection model) and the ordered probit (outcome model) regressions, respectively.

In terms of our hypotheses, we expect that $\beta_1 > 0$ to verify that servitized firms are more likely to engage in the different stages of the smart product scale progression. Similarly, we also expect that $\beta_2 > 0$, that is, the adoption of AI-intensive strategies is positively correlated with technology investments to develop smart products. Finally, a positive result for the interaction terms between the servitization dummy and the variable linked to the adoption of an AI-intensive strategy ($\beta_{12} > 0$) would suggest that AI-driven digitally servitized firms are more likely to adopt technologies linked to smart product development processes.

4. Results

The results of the ordered probit with sample selection applied to the study's hypothesized framework are shown in Table 3. The table offers two specifications of the model linking variables of product strategy and firm characteristics with the production of smarter products by these manufacturers. In addition, the table presents the results of the probit regression (selection model) where offer integratedness is introduced as key independent variable to explain the level of connectedness of the sample firms' products. The existence of productive interdependency between producers and their clients is found to incite the digitalization of the firms' products.

The two outcome models presented in Table 3 limit their analysis to those observations producing products that have some form of digital

Table 3
Ordered probit with sample selection: Regression results for progression up the smart product scale.

	Selection model	Outcome model (1)	Outcome model (2)
	Coefficients (std. error)	Coefficients (std. error)	Coefficients (std. error)
Offer integratedness	0.29 (0.10)***		
Servitization		0.38 (0.17)**	0.25 (0.21)
AI-intensive strategy		0.47 (0.20)***	0.56 (0.36)
Servitization × AI-intensive strategy			0.46 (0.19)**
Firm size (ln employees)	0.08 (0.19)	−0.16 (0.26)	−0.14 (0.26)
Firm age (ln years)	0.04 (0.10)	0.13 (0.14)	0.13 (0.14)
Regional dummies	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes
Inverse Mills ratio (λ)		−2.20 (0.91)**	−2.25 (0.93)**
Cut 1		−1.48 (1.31)	−1.38 (1.32)
Cut 2		−0.98 (1.32)	−0.89 (1.32)
Cut 3		−0.59 (1.33)	−0.49 (1.33)
Intercept	−0.18 (0.76)		
Log pseudolikelihood	−329.75	−281.88	−280.70
Wald test (chi2)	58.34*** (*d.f.* = 33)	80.42*** (*d.f.* = 34)	81.82*** (*d.f.* = 35)
Pseudo R2	0.0930	0.0695	0.0734
VIF (min-max)	1.31 (1.07–2.10)	1.49 (1.07–4.34)	1.56 (1.10–4.34)
Observations	576	278	278

Robust standard errors are presented in brackets. *, **, *** indicates significance at the 10 %, 5 %, and 1 %, respectively.

connectedness. As only digitalized product according to the convened definitions of this study can potentially collect, process and learn (therefore allowing them to carry any sort of virtue considered as smart), producers of non-digitalized products are not selected in these regressions. While the first outcome model includes the key independent variables for the study's first and second hypotheses separately (servitization and AI strategy), the second iteration introduces the interaction of both these variables in accordance with the third hypothesis (H3).

From the results of the first outcome model in Table 3, we can observe how the implementation of servitization on the part of a manufacturer makes them significantly more likely to produce products that are higher up the smart product scale relative to those with digitalized products that are not following such a service-intensive strategy. The same is found when observing the impact of the use of AI-intensive strategies on the likeliness of producers to generate smarter products in terms of their progression towards full autonomy. These results therefore confirm the first two hypotheses H1 and H2.

From the second outcome model including the interaction term that crosses servitization with AI-intensive strategy, we find that the positive effect of servitization and AI-intensive strategies over the progression up the smart product scale comes exclusively from the joint implementation of these two strategies. This means that firms simultaneously implementing servitization and AI-intensive strategies are significantly more likely to produce smarter products. This is in accordance with the premise of DSI and the study's third hypothesis, H3. However, for those firms applying only one of these strategies, either servitization or AI, they are not found to be significantly associated with the progression in the production of analytically smarter products according to the results from the second outcome model. This suggests that while both strategies independently contribute to smarter product development (as confirmed in model 1), their joint implementation generates additional, amplified effects over the development of smarter products.

The results of the model's control variables indicate that firm characteristics, such-as firm size, age, location, or industry do not significantly influence the level of smartness of a manufacturer's products. Notice that such business-level characteristics do not distort the study's main findings.

To better illustrate the results of the study, Fig. 3 presents the predicted probabilities, for firms implementing servitization strategies, AI-intensive strategies, and both, associated with the production of products with smart characteristics that fit each stage of the smart product scale. These results are based on the average marginal effect of each strategy at each stage as compared to all other observed manufacturers with digitalized products. As such, it can be seen how the simultaneous adoption of a servitization and AI intensive strategy becomes especially effective to induce the production of products with the smartest optimization and autonomy capabilities.

5. Discussion and implications

The results of this study have important implications for both theory and practice. From the basis that rapid and profound technological changes are currently transforming every aspect of business strategy, production, and management, academic research is called upon to understand these changes and examine how such change is affecting current practice as well as elucidate what is and can be done to better adapt to such transformation (Brekke et al., 2024). From this perspective, the results of the study presented in this paper offer new theoretical postulates that help adjust the current body of knowledge in business management to these changes. Similarly, the paper's findings add to the practical guidelines that can contribute to practitioners' understanding of these transformative changes and facilitate better managerial response and alignment.

5.1. Academic implications

The results of the study follow a recent line of research operating at the cross-roads of servitization and digitalization research which is quickly consolidating itself around the digital service innovation and digital servitization concepts (Favoretto et al., 2022; Filosa et al., 2025; Jia et al., 2024; Kohtamäki et al., 2019, 2020, 2021; Kowalkowski et al., 2013; Opazo Basáez et al., 2022; Rojas-Segura et al., 2023; Tronvoll et al., 2020). DSI and digital servitization, though interconnected, represent distinct elements of a firm's evolution toward digitally enabled service-based strategies. Digital servitization involves the transformation from selling standalone products to offering integrated product-service solutions, using digital technologies to enhance customer value and engagement. It marks a strategic shift in how firms structure their offerings and business models (Kohtamäki et al., 2019, 2025; Vaillant et al., 2025). DSI, by contrast, centres on the creation of entirely new digital services or the enhancement of existing ones through technologies such as AI, IoT, and cloud computing (Opazo Basáez et al., 2024). DSI acts as a catalyst for digital servitization by

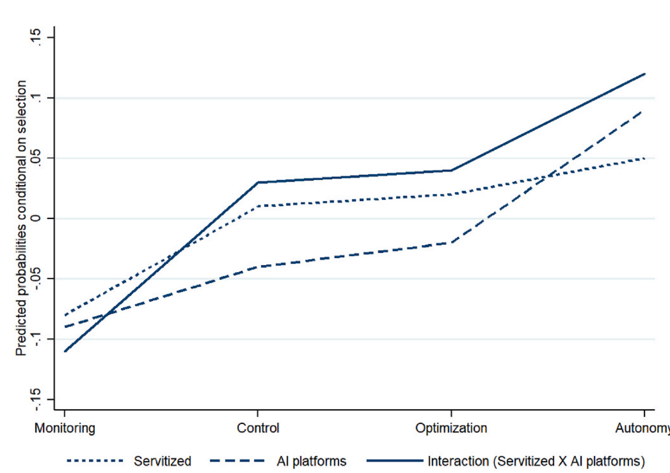

Fig. 3. Ordered probit model results: Smart product scale progression.

enabling smarter, more adaptive service offerings, and as was found in this study, allows manufacturers to produce products with more advanced analytically 'smart' capabilities. The study presented in this paper adds new perspective to the DSI literature by bringing in the role of smart products for attaining such DSI-enabled high-value outputs and the importance of service-intensive as well as AI-intensive strategies in inducing manufacturers to generate products with more advanced and autonomous smart products.

These findings can also be interpreted from a service-dominant logic where smart products evolve when both service-based business logic and AI-enabled knowledge systems are combined to allow dynamic value co-creation (Vargo and Lusch, 2017). From a dynamic capability perspective, the higher-order dynamic capabilities necessary for evolving products into autonomous learning systems require the joint implementation of solution-based service-oriented capabilities and AI-enabled digital sensing and learning capabilities (Coreynen et al., 2020; Sjödin et al., 2023). From a product autonomy framework, servitization ensures continuous interactive feedback loops within the value system and AI provides the data analytics and decisional autonomy, where the cognitive capacity of AI and service logic of servitization are required for products to operate independently while maintaining value co-creation (Bustinza et al., 2024). Finally, from the digital servitization theoretical perspective, servitization provides the business model and customer interface that can help firms transition their products towards smarter analytical abilities when coupled with the intelligence and autonomy engine accessible through AI (Kohtamäki et al., 2022, 2024).

Instead of limiting itself to the increasingly common 'digitalization' of manufacturing, the study centred more precisely on the specific impact of AI and AI intensive organisational and productive strategies implemented by manufacturers to better understand the propensities towards smarter product development (Raff et al., 2020). Recent studies in servitization have called for greater research on the specificities of the capacity-generating potential of AI-augmented servitization (Ayala et al., 2025b; Bustinza et al., 2024; Kohtamäki et al., 2025; Lafuente and Sallan, 2024). This paper not only answers these calls but also brings in the separate, though highly overlapping, smart product literature (Berente et al., 2015, 2021; Raff et al., 2020; Rijsdijk and Hultink, 2009; Vendrell-Herrero et al., 2021). As such, the study has shown that the DSI framework is adequate for the study of the overlaps between AI and servitization and has demonstrated, in line with DSI premise, that instead of an either/or analysis, when it comes to comparing servitization and AI intensive strategies for manufacturers, the analysis should rather be based on the impacts of mutual interactions between these two lines of strategic policy. To induce smarter products, manufacturers require AI-augmented DSI.

Such inference falls in line with the configurative view of technology within organisations and its role in value creation proposed by Orlikowski (1992) in his structurational model of technology. This approach views technology as both an external structuring factor for the organisation and the result of strategic choice and human action. As such, AI is not just a technology and servitization not just a production technique. They are both part of a wider strategic value generation system that can be at the core of the idiosyncratic capabilities that give a product its 'smart' character. Manufacturers that are better able to configure the role of technology and their service delivery in sync with their product's value generation system will be able to create differentiated value, service innovation, and system (re)formation (Akaka and Vargo, 2014; Mekalef, 2023). In the case of smart products, this means the progression along the analytical capacity of the product towards autonomous value maximisation.

Therefore, it is probably not enough for researchers to individually measure the presence and use of technologies (e.g. AI) and production techniques (e.g. digital servitization) to gain an understanding of the strategic and competitive value of these factors for manufacturers of smart products. Rather, a more complex configurational synthesis approach beyond single factor analytical research is likely to offer a better understanding of the productive mechanism that influence the 'smart' capabilities of products and their value generation potential.

The results of the study also offer support to the nested scale of smart product capabilities originally proposed by Porter and Heppelmann (2014). More recent research on the subject had tended to drop the nested progression character from their smart capability categorizations (Bohnsack et al., 2024; Rabetino et al., 2024; Raff et al., 2020). As such, the paper's findings show the importance of the technification of products as an output measure. By doing so, the study was able to highlight that the customer benefits associated with advanced digital servitization and AI are often dependent on the technification of the products supplied.

5.2. Managerial implications

There are several important applied implications to the findings of the study. As manufacturers strive to gain and maintain competitiveness in the new digital age of production, their transition towards producing higher value intelligent products is found to pass through the simultaneous adoption of both a service-intensive (Bustinza et al., 2024) and AI-intensive strategies (Ayala et al., 2025b). Adopting these strategies produces positive effects on the production of analytically smart product that progress towards autonomy (Opazo Basáez et al., 2024; Rabetino et al., 2024). Indeed, advanced servitization and AI are two parts of the same coin that are both essential for the production of ever smarter optimizing and autonomous products able to offer high-value solutions that go beyond the capability frontiers of the simple digitalized products in themselves (Huikkola et al., 2022a, 2022b).

It has been observed from previous research adopting a DSI approach that servitization and AI strategies were mutually beneficial (Kohtamäki et al., 2021), where the implementation of advanced servitization on the part of manufacturers is dependent on concurrent AI-intensive policies and vice-versa. The findings of this study go one step further and show that the mutual adoption of these strategies by manufacturers is likely to facilitate their development of smarter products in terms of their progression towards fully autonomous smart products (Berente et al., 2021; Raff et al., 2020; Vendrell-Herrero et al., 2021).

Vaillant et al. (2025) make a call for more prescriptive managerial implications from research to help managers keep pace with the rapid technological advances. For this, greater applied experimentation and more benchmark examples of what works and what does not are needed (Bazerman, 2005). The study identifies that the convergence of servitization and AI presents concrete opportunities for manufacturers to enhance their business offerings. By embedding AI capabilities into products, firms can enable real-time data collection, remote monitoring, and self-optimizing functionalities that increase responsiveness and performance in complex, fast-changing environments (Burton et al., 2024; Beverungen et al., 2021; Porter and Heppelmann, 2015). These capabilities allow businesses to shift from selling static products to delivering adaptive, intelligent services that evolve with customer needs (Kohtamäki et al., 2022). The strategic integration of AI insights with service-based models drives product innovation and helps firms differentiate themselves through dynamic, user-focused solutions (Vaillant et al., 2025a,b). In practice, this means manufacturers can boost customer value, unlock new revenue streams, and achieve greater operational efficiency by leveraging AI-enhanced DSI to transform their product-service systems (Kohtamäki et al., 2025).

Deductions from these results would tend to indicate that R&D or licensing investments on the part of manufacturers aimed towards generating smart capabilities for their products may not necessarily reach the desired objectives if the firm has not previously consolidated its service-intensive and AI-driven capacity needed to do so (Chowdhury et al., 2018; Schulz et al., 2023).

6. Concluding remarks and future research

6.1. Conclusions

This paper investigated whether manufacturers that simultaneously integrate both servitization and AI-intensive strategies are more likely to develop products with more advanced analytically 'smart' capabilities in terms of their progression through the stages of monitoring, control, optimization, and autonomy. To do this the study used a unique dataset collected via a specialized survey, comprising responses from 576 Spanish manufacturing firms in 2023. The findings, derived from an ordered probit model with sample selection, reveal that while both servitization and AI-intensive strategies contribute to the development of analytically smarter products, their significant impact is greater when these strategies are implemented together. Such findings align with the structurational model in considering value from technology as the result of holistic coherence between technology, strategy, service, and offer (Akaka and Vargo, 2014; Mekalef, 2023; Orlikowski, 1992). It adds to the principles of Digital Service Innovation (DSI) by underscoring the necessity of combining service-oriented and AI-driven approaches to advance smart product capabilities toward full autonomy.

6.2. Limitations and further research

The findings of the research reported in this paper are open to further corroboration. First, our study focuses on whether servitization and AI-driven strategies impact the level of smart capabilities that manufacturers introduce to their products. While prior studies support the operationalization of our analysis from the company-wide perspective, future work would ideally narrow-down the study at a product-specific level, recognizing that firms may adopt distinct strategies across their different product lines, which can translate in varying levels of smartness from one product to another.

A second area where future research can build upon this study would be by adding financial metrics to the output analysis. The study innovates by introducing the importance of the technification of products as an output measure in terms of its progression up the smart product capability scale. From this point, an analysis of the economic performance impact of doing so could further develop on the insights introduced from our research.

Third, the quantitative approach adopted in the study allowed us to understand if there are connections between service-intensive and/or AI-intensive strategy implementation and the development of smarter products by manufacturers. Working upon these findings, future qualitative studies could extend the analysis further by investigating the mechanisms at work across these relations, as well as exploring how differences in organizational governance, specific service strategies, or particular types of AI impact the development of products with smarter autonomous capabilities. The cross-sectional nature of the study's data does not allow for longitudinal analyses. As a result, future longitudinal work seems necessary to better understand the temporal dynamics of the connections between servitization, AI use and the propensity of manufacturers to increase the analytical capacity of their products up the smart capability scale. Likewise, the conclusions drawn from this study emerge from a sample of Spanish manufacturing companies. We believe that our findings and recommendations can be extended to organisations and products in different geographic settings.

Finally, our results indicate that the majority of manufacturers are currently producing unconnected products, and of those that claim that their products are digitally enhanced, only a minority carries any sort of 'smart' virtue (45 % of digitalized products and 21.7 % of all observation). Only 6.6 % of surveyed firms have given their products autonomous smart capabilities. Autonomy-enabled products remain a concern primarily for early adopters (McElheran et al., 2024) and as servitization and AI adoption rates continue to rise, further analysis will shed greater light on the specificities of their relationship with the production of smarter high value adding products.

Table A1
Non-response and early response bias tests

	1) Non-response bias			2) Early response bias		
	Final sample surveys	Incomplete surveys	Mann-Whitney *U* test	Early wave (first 10 %)	Late wave (last 10 %)	Mann-Whitney *U* test
Monitoring sensors	0.23 (0.42)	0.11 (0.32)	1.791 (*p*-value = 0.07)	0.27 (0.45)	0.21 (0.41)	0.711 (*p*-value = 0.48)
Control software	0.15 (0.36)	0.12 (0.24)	0.640 (*p*-value = 0.69)	0.20 (0.40)	0.26 (0.37)	0.534 (*p*-value = 0.59)
Optimization algorithms	0.10 (0.30)	0.08 (0.14)	1.081 (*p*-value = 0.37)	0.11 (0.31)	0.11 (0.31)	0.032 (*p*-value = 0.97)
Autonomous product	0.09 (0.29)	0.07 (0.14)	1.800 (*p*-value = 0.07)	0.09 (0.29)	0.10 (0.31)	−0.285 (*p*-value = 0.78)
Servitization	0.73 (0.44)	0.78 (0.38)	−1.534 (*p*-value = 0.14)	0.70 (0.46)	0.67 (0.48)	0.338 (*p*-value = 0.74)
AI-intensive strategy	0.25 (0.43)	0.17 (0.38)	1.294 (*p*-value = 0.20)	0.29 (0.46)	0.26 (0.44)	0.267 (*p*-value = 0.79)
Digitalized product	0.48 (0.49)	0.52 (0.50)	−0.620 (*p*-value = 0.54)	0.51 (0.49)	0.46 (0.50)	1.220 (*p*-value = 0.22)
Offer integratedness	5.12 (2.09)	4.83 (2.11)	1.015 (*p*-value = 0.31)	4.73 (2.30)	4.72 (2.20)	0.106 (*p*-value = 0.92)
Firm size (employees)	34.90 (22.80)	40.02 (40.06)	−0.236 (*p*-value = 0.81)	45.59 (56.08)	22.19 (10.77)	4.247 (*p*-value< 0.00)
Firm age (years)	30.30 (16.11)	36.34 (13.94)	−0.881 (*p*-value = 0.38)	33.13 (18.91)	29.11 (15.36)	1.814 (*p*-value = 0.06)
Observations	576	44[(a)]		57	57	

Note (a): for offer integratedness the sub-sample of incomplete surveys is 38. Standard deviation is in parentheses. *, **, *** = significant at the 10 %, 5 %, and 1 % levels, respectively (Mann-Whitney *U* test).

CRediT authorship contribution statement

Esteban Lafuente: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yancy Vaillant:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Investigation, Funding acquisition, Data curation, Conceptualization. **Ajax Persaud:** Writing – review & editing, Writing – original draft, Visualization, Validation, Investigation.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors made minor use of Deeple and ChatGPT in order to improve language and readability of certain sections of the manuscript. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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