The impact of artificial intelligence capabilities on servitization: The moderating role of absorptive capacity-A dynamic capabilities perspective

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A B S T R A C T

The advent of artificial intelligence (AI)-based technologies has opened new opportunities for manufacturers to maintain their technological edge and address pressing societal challenges. This research investigates the nature of the relationships between AI capabilities, servitization, and the role of absorptive capacity. Building on dynamic capabilities literature, we developed and empirically tested a model using structural equation modeling (SEM) and further applied a fuzzy-set qualitative comparative analysis (fsQCA). Through the construct of AI capabilities and its four sub-dimensions, we find supportive evidence from our model estimates employing data from 185 manufacturing firms in the US and EU. The study findings highlight the positive impact of AI capabilities on servitization; this relationship is positively moderated by absorptive capacity. Furthermore, the road to servitization is through advancing AI capabilities related to internal process and resource optimization coupled with AI for social innovation services. The study's theoretical and pragmatic implications are discussed.

Keywords: Artificial intelligence; servitization; social innovation; fuzzy set qualitative comparative analysis (fsQCA); dynamic capabilities.

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1. INTRODUCTION

A burning question for servitization researchers and practitioners is how artificial intelligence (AI) can be incorporated to enhance operational efficiency, market offerings, customer experience, and social innovation (Haefner et al., 2021). Therefore, AI is increasingly becoming a focal point for manufacturers' innovation debate, which is in line with the main challenges articulated and enriched by B2B marketing theory, in terms of technology advancement, value creation, analytics, and overall ecosystem innovation (Mora Cortez & Johnston, 2017).

In the B2B context, firms have widely viewed servitization as "a transformational process whereby a company shifts from a product-centric to a service-centric business model and logic" (Kowalkowski et al., 2017a, p. 8). Foundational research in this area has identified the servitization business model configuration (Palo et al., 2019), categories of resources and capabilities that must underpin the transition to services (Baines & Lightfoot, 2014; Dmitrijeva et al., 2020; Kanninen et al., 2017b; Ulaga & Reinartz, 2011). Another stream of servitization literature has argued that servitization increasingly constitutes a sociotechnical dimension that must be addressed in the current business ecosystem buzzing with sustainability incentives, intelligent decarbonization solutions, and powerful government regulations (Huntingford et al., 2019; Spring & Araujo, 2017).

Current development in machine learning (ML) and AI have supercharged the innovation process and service breakthroughs, which has far-reaching business and societal consequences. This AI development is driven by the explosion in available and accessible data warehouses, along with sensor connectivity data facilitated by the internet of things (IoT), which, in some cases, leads to digital servitization (Kohtamäki et al., 2019). Therefore, AI should be valued as a business capability rather than a mere technological advancement (Davenport & Ronanki, 2018). Capabilities can be defined as “complex bundles of skills and accumulated knowledge, exercised through organizational processes, that enable firms to coordinate activities and make use of their assets” (Day, 1994 p.38). Therefore, data are a valuable asset that can help in building the enterprise AI ecosystem that enhances service innovation.

Despite the growing body of literature which sporadically examines the strategic value of digital transformation on a company service transition (Abou-foul et al., 2021; Gebauer et al., 2021; Mikalef & Gupta, 2021) there are still debates about the potential of AI capabilities -as an imperative extension to digital transformation and its business-to-business (B2B) organizational constitutions and configurations (Sjödin et al., 2021).

One source of these debates is the fact that the use of broad information technology constructs coupled with the availability of successive generations of new technologies precluded the advancement of consistent, explicit, readily comparable empirical studies on the interdependencies between AI artifacts and servitization, rendering previous research impractical (Desouza et al., 2020; Mikalef & Gupta, 2021). Additionally, the literature mostly viewed technological capabilities from an inward perspective arising from the IT division, without considering the role of business customers in strategically harnessing technological capabilities, resulting in a widening gap in the literature concerning the conceptual association of AI with other theoretical aspects. Confounding the debates further is the fact that popular AI capabilities literature focuses on firm-level analysis, which, in some cases, obscures the real impact of AI on specific business processes and limits our understanding of its theoretical and practical interconnections (Iansiti & Lakhani, 2020; Kohtamäki et al., 2019). Prior literature also fails to identify those higher-order dynamic capabilities required to successfully change and adapt (Teece, 2007) to avoid the infamous competency trap (Barnett & Pontikes, 2008).

The convergence of advanced cognitive computing manifested in AI technologies and servitization shows that the latter represents a good example of the successful implementation of the former (Agarwal et al., 2022). The scholarly interest in the impact of AI on servitization is still embryonic and lacks empirical evidence (Wirtz et al., 2018), the central premise of AI and machine learning is that it can enhance efficiency and better customization for value proposition (Haefner et al., 2021), with the vast majority of servitization research built on the interpretation of the radical transformation process while continuing to stress innovation and technology implementation that supports the creation of value-added (Garcia Martin et al., 2019). To date, AI has been widely viewed as a radical source of reform of patterns of production and enhancing the learning process that complements decision support systems in place (Kasie et al., 2017; Mikalef & Gupta, 2021). AI impact on service provision is still underdeveloped as advancing a firm’s AI capabilities requires an incremental investment in complex technology and a delicate balance between centripetal forces that push manufacturers’ activities toward integration and centrifugal forces that pull value proposition out into the market in a customer-driven fashion, which creates an evolution in the services ecosystem in development (Holgersson et al., 2022).

AI in the industrial marketing context is widely viewed as a knowledge-based system, yet it is not clear whether manufacturers’ efforts to acquire, assimilate, and exploit new knowledge would play a role in the advancement of servitization and AI, warranting a joint investigation of these perspectives and their optimal configuration (Valtakoski, 2017).

To address these literature contentions, first, this study develops the AI capabilities construct (as opposed to the IT capabilities construct). As discussed in Section 2, we propose the notion of AI capabilities consisting of four components: (1) AI for customer value proposition, (2) AI for key processes optimization, (3) AI for key resources optimization, and (4) AI for societal good; and we have provided a measurement scale for this construct. Second, building on dynamic capability theory (DCT), this study introduces and develops a theoretical framework delineating the mechanism by which AI capabilities leverage servitization, taking into consideration how AI affects specific organizational processes. Furthermore, we have yet to understand the institutionalization of absorptive capacity and its interactive effect on the relationship between AI capabilities and servitization. Third, we apply both covariance-based structural equation modeling (CBSEM) and a fuzzy-set qualitative comparative analysis (fsQCA) to assess the net and combinatorial effects of the proposed four components of AI capabilities on servitization, which leads to better development of the theoretical parsimony of AI- servitization configurations. Consequently, this combination of both techniques can greatly enhance our understanding of the underlying complex reality in this configuration, paving the way to important data that inform practitioners and decision-makers in terms of finding patterns and optimal configurations that leverage servitization.

The paper proceeds as follows: the next section reviews the theoretical underpinnings of servitization, AI capabilities, and absorptive capacity, as well as the hypothesized relationships. Section 3 describes the research methodology with construct operationalization. Section 4 presents the study's analyses and the results of the proposed structural model. Section 5 discusses the research findings and dwells on their theoretical and pragmatic ramifications and, finally, the study concludes by examining research limitations and future avenues of research.

2. THEORY AND HYPOTHESES

2.1 The dynamic capabilities perspective

The main premise of dynamic capabilities theory (DCT) is that, for companies to achieve superior performance in volatile industries, they must possess higher-order capabilities – namely, adaptive processes and structures that enable them to change their baseline capabilities so that they can sense, seize, and adapt to an ever-evolving competitive landscape (Felin & Powell, 2016). Teece (2007) advanced the threefold classification of firm-level dynamic capabilities, namely sensing, seizing, and reconfiguring, required to reach the optimal enterprise structure, continuous innovation anticipation, and knowledge management. While the business landscape is shifting to more data-driven enterprises, AI cognitive applications on the lower end of the spectrum are altering customer value propositions, and operational efficiency, but, more importantly, they are helping to tackle real business problems and pressing society challenges (Dangelico et al., 2016).

Following this line of argumentation, we maintain that cognitive technologies are a source of idiosyncratic, higher-order capabilities and ultimately impact the micro-foundation of the dynamic capabilities framework because it helps companies change their baseline capabilities in areas such as product design, customer service, and manufacturing processes. In this regard, we are echoing the view of Hercheui and Ranjith (2020) in which they found that the diffusion of AI capabilities in manufacturing affects the dynamic capabilities of organizations in terms of the firm's ability to sense rapid industry changes, seize opportunities in terms of more personalized customer value proposition and reconfigure the use of internal process and resources for speed and cost-cutting in the transformational process of digital servitization (Tronvoll et al., 2020). Furthermore, literature has conceptualized firm capabilities as a hierarchy; therefore, for manufacturing firms to achieve dynamic capabilities, they need to efficiently exploit their current, lower-order capabilities, in terms of systems, assets, and competencies they have acquired while operating (Slotegraaf, 2007). Previous research has highlighted the importance of dynamic capabilities in advancing servitization processes (Coreynen et al., 2020; Fischer et al., 2010; Kanninen et al., 2017a), but it has fallen short of addressing the AI capabilities required to achieve servitization in terms of the optimal configuration for endogenous and exogenous resources needed to improve the manufacturing business model and business-process redesign.

The intersection between dynamic capabilities literature, B2B marketing and information system (IS) research, indicates that a potentially transformative technology such as AI is imperative for companies seeking new competitive advantage, that leads to unlocking new business models by sensing opportunities in new technologies and seizing the new revenue streams related to those technologies, which requires reconfiguration and realignment of firms' resources, structure, and strategy (Teece, 2023). AI as an extension to information technologies can help in exploring and exploiting firms' dynamic capabilities related to process, supplier, and alliances building, operations, and marketing that impact overall performance (Majhi et al., 2021).

Following the strategic orientation of dynamic capability literature, one can argue that advancing both servitization and AI capabilities requires a process of change, guided by the micro-foundations of DCT. For instance, trained machine learning models can help in sensing new opportunities or threats; seizing new opportunities through the integration of intelligence capabilities targeted to innovate business models (Lee et al., 2019); and finally transforming existing business model configurations by resource realignment and optimization to leverage transformative social progress (Toma et al., 2020). Prior IS literature also expanded the dialogue of the transformative value of AI as a firm-specific complementary (Nishant et al., 2020).

In addition, DCT is built on the premise of organizational learning abilities that leverage innovation and that deliver more customized servitized offers. Screening external environments for new knowledge and continuous assimilation, transformation, and exploitation of such market knowledge enhance a firm's responsiveness and operational agility, making absorptive capacity an important type of dynamic capability that impacts servitization processes (Malhotra et al., 2005; Wheeler, 2002).

2.2 Conceptual framework and hypotheses development

Figure 1 presents the research model, while Table 1 shows the operational definitions of the research model constructs.

{INSERT TABLE 1 HERE}

{INSERT FIGURE 1 HERE}

2.2.1 AI capabilities and servitization

Mikalef and Gupta, (2021) define artificial intelligence as "the ability of a system to identify, interpret, make inferences, and learn from data to achieve predetermined organizational and societal goals" (p. 3).

Artificial intelligence, therefore, constitutes an interdisciplinary field that opens a new horizon of opportunities that have practical implications for both businesses and society as a whole. Despite the great attention this field of research has drawn from both researchers and practitioners, its ultimate uses and applications are still to a certain extent new and over-promised (Bughin et al., 2017). To cut through the hype, AI is built on the advancement of machine learning (ML) capabilities using a vast amount of structured and/or unstructured data to mimic a certain level of human cognitive ability (Smith, 2019). Arthur Samuel, a pioneering figure in ML, conceptualized it as a field of study that gives computers the ability to learn without being explicitly programmed (Samuel, 1959), giving rise to the variety of self-learning algorithms and knowledge acquisition platforms that make up the backbone of modern expert systems. It is noteworthy that, while the terms 'AI' and 'data' science are widely used interchangeably in the industry, they are distinct and widely overlapped. Data science helps in extracting knowledge and insights from data, using statistical techniques to support decision-making (Provost & Fawcett, 2013).

The widely used AI in the public domain is known as artificial narrow intelligence (ANI) (Rosa et al., 2016). Wirtz et al. (2018) categorized AI capabilities that are widely used in business applications, ranging from AI process automation systems; virtual agents; predictive analytics and data visualization; cognitive robotics and autonomous systems; intelligent digital assistants (IDA); cognitive security analytics and threat intelligence; identity analytics; edge analytics; and finally, machine vision and sensing. In the same vein, Sjödin et al. (2020a) classified AI capabilities in a digitally servitized manufacturing context into data pipeline capabilities, algorithm development capabilities, AI democratization capabilities customer co-creation capabilities, and data-driven delivery operation. In addition, IS literature also classified the value types of AI applications in terms of process automation, cognitive insights, and cognitive engagement (Collins et al., 2021). However, the prior literature on the operationalization and conceptualization of AI capabilities still lacks some dimensions related to sustainability and value proposition co-creation (Nishant et al., 2020; Vinuesa et al., 2020). In this research, we take these classifications further. Building on both AI and business model literature (Hercheui & Ranjith, 2020; Johnson et al., 2008; Teece, 2010), we argue that AI capabilities can be divided into four categories: those which advance the customer value proposition (sensing and seizing capabilities), those which help in optimizing key business processes, those which help in optimizing key resources (transforming capabilities), and finally those which enhance societal good (Day & Schoemaker, 2016).

The main promise of AI and data science is to provide managers with actionable insights that help them enhance their business value, anticipate customer preferences, and more accurately price their market offerings. Researchers have found that manufacturing firms using deep learning personalization algorithms achieved better customer success and more profitable servitized offerings (Dubé & Misra, 2019), implying a positive relationship between AI capabilities targeting customer value propositions and digital servitization (Davenport et al., 2020; Rachinger et al., 2019; Ritter & Lund, 2020). Furthermore, prior research has hinted at the positive impact of algorithmic pricing on service success (Assad et al., 2021). The introduction of AI that predicts future trends has had a positive impact on delivering servitized offers such as predictive maintenance and asset management (Wang & Wang, 2017). In addition, AI is a strong enabler of business model innovation and digital servitization (Sjödin et al., 2021) allowing manufacturing firms to create value from servitization, building on the advancement of digital service innovation.

While the servitization process is viewed as an outcome of digital service innovation (Raddats et al., 2022), AI capabilities such as using and analyzing big data can hugely impact the customization part of service design and delivery, especially in value-based pricing and predictive maintenance services. Furthermore, in looking for growth, manufacturers opt to apply AI to optimize, personalize and transform every customer touchpoint, and use AI to enhance value proposition manifested in advancing service call scheduling and new service recommendations that require capturing, analyzing, and utilizing customer data to sense, shape and optimize customers' experience, leading to better marketing capabilities (Ameen et al., 2021; Mora Cortez & Johnston, 2018). In the B2B context, AI has also been found to allow manufacturers to understand the specific granular requirement deemed necessary to deliver more servitized offers in a more customer-driven use cases fashion (Kushwaha et al., 2021). Therefore, AI related to enhancing customer value propositions has been found to have a positive impact on servitization processes in terms of designing relevant, outcome-based contracts, leading to better customer service, and customer engagement (Kumar et al., 2021). Syam and Sharma (2018) found a positive impact of AI capabilities and machine learning on servitization success, stemming from the breakthroughs achieved by gathering real-time data from the sales processes and collecting actionable after-sales insights.

AI's applications and capabilities related to process optimization are profoundly useful for businesses looking to increase efficiency, improve uptime using predictive asset maintenance, cut costs, improve process reliability, execute business model renewal, and enhance yield optimization, which leads to better-servitized market offerings (Baines et al., 2009; Baines & Lightfoot, 2014). IS literature argues that AI for process efficiency can help augment human intelligence using appropriate ML models, especially in repetitive routine tasks, leading to more integration between humans and AI that helps in overcoming some cognitive limitations inherited in humans (Enholm et al., 2021). AI applications for process control and optimization can hugely enhance manufacturing scheduling, multi-period planning, and real-time optimization, which can lead to better service delivery in terms of quality and flexibility. Furthermore, the use of data rectification by extracting meaningful features from collected data can help AI applications in predictive modeling, fault detection, process optimization, and control (Thon et al., 2021). The use of AI applications in process optimization and control has a positive impact on digital servitization and value co-creation (Boehmer et al., 2020; Paiola & Gebauer, 2020).

Consequently, AI capabilities related to resource optimization can facilitate internal and external resource allocation and supplier sourcing, leading to a reduction in service waiting time and other administrative issues. It is noteworthy to draw some distinctions between AI applications for process optimization and AI applications for resource optimization in the manufacturing context, in which the former is more related to generating action recommendations in real time to avoid any benchmark deviation, ensuring better performance monitoring, error detection, and reduction, and economic optimization, enhancing overall effectiveness and efficiency. The latter, on the other hand, is more about optimizing internal resources and manufacturer’s workloads by better resource orchestration in terms of resource coordination, leverage, and deployment; it also includes the optimization of the inter-firm resources, which involves suppliers’ networks, distributors, and external data warehouses, which enhance parties’ collaboration, inventory prediction, labor productivity, and data governance to achieve higher efficiency. Previous servitization literature shed some light on the positive impact of specialized AI platforms for resource and process optimization on servitization (Barbieri et al., 2021). Therefore, AI capabilities targeting resource optimization are fundamental for smart servitization success (Coreynen et al., 2017; Huikkola et al., 2016;

Sjödin et al., 2021). Parallel to this, Klumpp (2018) found a positive impact from AI targeting logistic and service provision transition. Empirical research has also concluded that AI and robotics are fundamental to fostering process automation, which positively impacts servitization (Blöcher & Alt, 2020). Suppatvech et al. (2019) stressed the importance of using AI applications and IOT to increase resource utilization to support servitization activities, added to which Zhang et al. (2020) found that using Artificial Intelligence/Machine Learning (AI/ML) dedicated to resource optimization, automation and orchestration can positively impact Product–Service System (PSS), by enhancing resource elasticity and configuration, helping manufacturers to streamline workflow and pipelines to deliver service solutions in minimum time, cost and maximum reliability.

While the literature has widely ignored the social impact of servitization (Doni et al., 2019), those AI capabilities that tackle sustainability issues and decarbonization solutions are highly important from a customer's perspective (Bag et al., 2021; Chandy et al., 2021). Customers' pull and regulatory bodies' push exert high pressure on companies to strategically think about providing servitized offers that tackle climate change challenges. Current literature on industrial marketing has found a positive impact of AI on climate-driven service analytics capabilities, as well as service innovation and performance (Akter et al., 2021). As a driver of servitization, AI plays a significant role in advancing social innovation capabilities, which help to reduce carbon emissions through smart energy management services, safety assistant agents using deep reinforcement learning, and effective waste management services that apply complex data science analytics (Calabrese et al., 2018; Vázquez-Canteli & Nagy, 2019). Previous literature has also highlighted the importance of AI capabilities to provide manufacturers with more sustainable smart supply chains (Sanders et al., 2019); the data-driven approach to supply chain management and manufacturing could not be materialized without the advancement in ML and core predictive models that manage risk and increase sustainable market offerings (Tseng et al., 2021). The impact of AI applications designed to advance sustainable causes has also been an enabler of service innovation and solutions (van Wynsberghe, 2021). AI also can help to manufacture enhance resource efficiency, which positively impacts the ecological performance of manufacturers (Waltersmann et al., 2021).

Taken together, the previous arguments indicate that overarching AI capabilities most likely have a positive impact on servitization. Therefore, we stipulate the following hypotheses:

H1. A firm's AI capabilities are positively related to servitization.

H1a. A firm's AI capabilities for customer value propositions are positively related to servitization.

H1b. A firm's AI capabilities for key process optimization are positively related to servitization.

H1c. A firm's AI capabilities for key resource optimization are positively related to servitization.

H1d. A firm's AI capabilities for societal good are positively related to servitization.

2.2.2 Moderating role of absorptive capacity

The concept of absorptive capacity, which emerged from the field of macroeconomics (Adler, 1965), emphasizes the ability of a company to commercially exploit, absorb, and assimilate external knowledge and resources. The notion of absorptive capacity encapsulates the importance of such capabilities to ensure a manufacturer's growth; this can be achieved by good execution of a unique set of intra-organizational routines and incremental adjustment and reconfiguration of the firm dynamic capabilities (Zahra & George, 2002). It could be argued that organizational learning capabilities are central to providing solutions to customers' problems (Davies et al., 2007). Therefore, external knowledge management is paramount from a capability perspective to ensure a smooth and effective service transition which requires micro-vertical integration within different partners in a servitized context (Todorova & Durisin, 2007). Current literature has classified absorptive capacity as a dynamic capability (Malhotra et al., 2005; Pavlou & Sawy, 2006), and companies with higher degrees of absorptive capacity can utilize knowledge-based assets more efficiently, sensing technological changes and work to reconfigure functional capabilities to create better market offerings.

Consequently, the success of service innovation depends predominantly upon the firm's level of absorptive capacities. Customers' data can be internalized and funneled into machine learning models to create more comprehensive consumer profiles, better insights, better-customized propositions, and better customer experiences (Wilson & Daugherty, 2018). On the one hand, this creates opportunities for firms to shift to service provision by acquiring the cognitive technological capabilities required to deliver servitized offers such as AI capabilities (Mikalef et al., 2021). The capacity to absorb external knowledge is considered an important organizational antecedent in which ambidexterity literature unearthed a positive relationship between absorptive capacity, service transition, and business model adaptation (Kranz et al., 2016). Manufacturers with high levels of absorptive capacity can easily sense new opportunities and create value by enhancing servitized offers. Heterogeneity in absorptive capacity levels -low versus high- plays a vital role in operational efficiency and the embeddedness of new technologies deemed paramount to the servitization process (Escribano et al., 2009). Rothaermel and Alexandre (2009) found that absorptive capacity exerts a positive moderating effect on a company's technology capabilities and service provision performance. In addition, Zhang et al. (2018) found a positive effect of IT capabilities on product and service innovation, which is mediated by absorptive capacity. Empirical research has also found that absorptive capacity moderates the relationship between process innovation and service innovation (Ahlin et al., 2014), while also moderating the relationship between strategic collaboration —facilitated by AI advancement— and digital transformation (Siachou et al., 2021). Therefore, given the discussion above and the empirical evidence from prior literature, we postulate the following hypothesis:

H2. A firm's absorptive capacity moderates the relationship between AI capabilities and servitization. Specifically, the relationship diminishes under conditions of low absorptive capacity and becomes stronger as absorptive capacity increases.

3 METHOD

3.1 Data collection and sample decomposition

Consistent with previous research (e.g., Wales et al., 2013), this study collects both secondary data by leveraging the OSIRIS database and perceptual data —respondent survey— from a sample consisting of manufacturing firms in the United States (58%) and the European Union (42%). Table 2 shows the demographic characteristics of our research sample. We purposely chose a wide range of firms in different industries for two reasons. First, doing so accounts for those firms which are undergoing digital transformations and also offer sufficient service solutions (Fang et al., 2008). Secondly, this method enhances the generalizability of the research findings. The self-administrated online survey was developed and fielded over a period of nine weeks and was sent to 584 prospect companies identified as belonging to a potential target audience, and respective key informants were identified based on their possession of sufficient knowledge about the research context and their appropriate involvement in steering decision-making with a good overview of the entire firm (Kumar et al., 1993). Professional social media platform groups such as Artificial Intelligence and Business Analytics (AIBA) on LinkedIn were used to identify prospective respondents in targeted companies. Further filtering criteria and validation items were included in the survey instrument to further isolate both the correct key informants and servitized firms. Three weeks after the initial online invitation, Dillman's (2011) follow-up protocol was used to enhance the response rate by targeting those subjects who failed to return a usable questionnaire. A total of 185 fully usable questionnaires were received and included in the final data set, with a response rate of 31.6%, in line with other response rates associated with organizational research (Tippins & Sohi, 2003).

Following Armstrong and Overton's (1977) recommendations, a test for a potential non-response bias was performed by splitting our sample answers for all study constructs — servitization, absorptive capacity, and the four dimensions of AI capabilities— into two groups: early and late respondents. The t. test resulted in no significant statistical difference between respondents and non-respondents. Furthermore, a one-way ANOVA was performed for all constructs between key informants with IT knowledge and those with other functional knowledge. The results obtained indicate no statistically significant differences between the two groups, with $p < 0.01$.

Furthermore, to assess the degree to which common method variance (CMV) might influence the study results, the researchers employed ex-ante remedies by Podsakoff et al. (2003), in terms of survey design, anonymous participation, and the use of reverse items, etc. The study also used Harman's single-factor test as an ex-post procedure. We subjected the study variables to a principal component factor analysis and varimax rotation with eigenvalues > 1.0. The test showed that six factors accounted for 74.38% of the variance, and the first factor accounted only for 21.39% of the variance, resulting in no dominant single factor emerging due to CMV. We also tested the variance inflation factor (VIF) for all items, with the highest VIF of 2.19 being well below the recommended threshold value of 4 (O'Brien, 2007). Therefore, it is safe to conclude that non-response bias, CMV, and multicollinearity are minimal and not serious concerns in this study.

{INSERT TABLE 2 HERE}

3.2 Measures

Appendix A shows the study's measurement scales. Some of the scales were adopted from previous literature, while AI capabilities are a novel construct with newly developed items.

3.2.1 Independent variable

3.2.1.1 The C-OAR-SE method for AICAP scale development

The novel construct of AI capabilities (AICAP), was developed by employing the C-OAR-SE method (Rossiter, 2002; Rossiter, 2011) which stands for construct definition, object classification, attribute classification, rater identification, scale formation, and enumeration. According to this method, a construct can be conceptualized according to an object (a focal object being rated), attribute (a dimension of judgment), and rater entity (the judges). In the first step, the study operationalized the AI capabilities construct while considering both the study's research design and its specific empirical context. In the construct definition stage, we have built on the working definition of AI capability (see Table 1 based on Mikalef and Gupta, 2021), we also broadened the definition to encapsulate different works in business model innovation, information management, and computer science that are closely related to the constitution of the AI capabilities conceptualization process (Johnson et al., 2008; LeCun et al., 2015; Wirtz et al., 2018; Yao et al., 2017; Zadeh, 1996). The object of the construct in this study is AI in manufacturing firms, an abstract formed object according to the C-OAR-SE method, while AI capabilities are a component of the AI object. Second, the attribute of AI capabilities is a second-order eliciting attribute encapsulating four components which are also eliciting attributes according to the C-OAR-SE framework. Third, the rater entities were selected and arranged to include a panel of three academics (in industrial marketing and AI) and 11 industry experts familiar with the concept of service innovation and AI and its practical applications in the manufacturing context. The first and the second steps were accomplished by an open-ended interview, during which, in step three, the identified rater entities (expert judges) ratified the main components of AICAP (Rossiter, 2002). Accordingly, AI capabilities are conceptualized as a reflective-reflective second-order construct following Jarvis et al.'s (2003) suggestion for construct types specifications. The components of the AICAP construct are as follows: (1) AI for customer value proposition (AICVP), (2) AI for key process optimization (AIKPO), (3) AI for key resource optimization (AIKRO), and (4) AI for societal good (AISGD).

Building on the aforementioned three steps, a total of 28 potential stem items (seven for each component) were formulated guided by a literature review and qualitative study using open-ended interviews with the selected rater entities, to formulate the items part of each component of AICAP and also to address any issues related to items' clarity and relevance to component definition (El & Akrout, 2020; Sabri & Obermiller, 2012)

The same panel has also been used in the fourth step of scale formation, in which the stems of the scale items were generated for pre-testing using the cognitive interviewing method with the raters panel (D. Collins, 2003). During this, experts' rating was used to establish AICAP content validity. As recommended by the C-OAR-SE method, content validity index (average I-CVI) was calculated for all AICAP dimensions, and the result for all items exceeded the cutoff value of 0.79 (Polit & Beck, 2006). However, eight items were rejected and deleted from the final measurement scale for receiving an I-CVI value below 0.70, ensuring AICAP content validity (Polit & Beck, 2006).

Finally, the AICAP was enumerated by deriving a total score from the scale items (Rossiter, 2002), in establishing construct reliability, the proportional reduction in loss (PRL) for inter-judge agreements was calculated (Rust & Cooil, 1994b). The results show that the proportion of inter-judge agreement for the panel was 0.86 between 11 judges (industry experts), creating a PRL coefficient of 1, thereby ensuring AICAP construct reliability (Rust & Cooil, 1994, p. 8, Table 4).

Taking into consideration the C-OAR-SE method recommendations when deploying the Likert scale format (see Rossiter, 2002, p. 322). This newly developed scale with its four main sub-dimensions was operationalized using a 5-point Likert ranging from "1—strongly disagree" to "5—strongly agree." Finally, and for more scale development rigor and parsimony, the use of

Rossiter's method for scale development -which relies on content validity- was coupled with the two steps approach recommended by Gerbing and Anderson, (1988) which entails performing Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). The EFA has been carried out to address the multidimensionality of the AI capabilities construct, using principal axis factoring and ProMax oblique rotation with eigenvalues > 1.0. The analysis yielded four main dimensions supporting the construct's theoretical conceptualization, and all items -except three- were loaded cleanly on their corresponding factors with loadings exceeding the cutoff value for the newly developed scale of 0.6 without any major cross-loading to report (Kline, 2014). Proceeding to the CFA stage, the single factor CFA indicates that three items were deemed to be not satisfactory due to high modification indices and were removed from the final items set (Bagozzi & Yi, 1988), leading to the unidimensional model to show acceptable goodness-of-fit indices, see Appendix B. Furthermore, all sub-dimensions scales yielded satisfactory levels of Cronbach's alpha ($\alpha > 0.70$) and a satisfactory level of average variance extracted (AVE), which was greater than the threshold level of 0.50, providing more evidence of the construct's reliability and convergent validity (Bagozzi & Yi, 1988). Additional validity tests were also performed using second-order factor analysis for the AICAP construct, and the study tested whether the AICAP sub-constructs could be aggregated into one main construct. Appendix B shows the confirmatory factor analysis (CFA) results, which provide good support for the sub-constructs aggregation into one second-order construct.

3.2.2 Dependent variables

The servitization construct (SERV) was measured using the scale proposed by Abou-foul et al. (2021). The study conceptualizes and operationalizes servitization as a higher-order construct that can be decomposed into three dimensions: top management service orientation, resource mobilization, and market offering. Each item was measured using a 5-point Likert scale ranging from "1—strongly disagree" to "5—strongly agree."

3.2.3 Moderating variables

The absorptive capacity (ACAP) scale items were adopted from Flatten et al. (2011) and operationalized using a 5-point Likert scale ranging from "1—strongly disagree" to "5—strongly agree." This study uses a shorter version of the original measurement scale on the aggregated level, following the recommendations of Sandy et al. (2016). The shorter version preserves the construct's theoretical domain and multidimensionality, and the scale used also encapsulates the four ACAP dimensions of knowledge acquisition, assimilation, transformation, and exploitation proposed by Zahra and George (2002).

3.2.4 Controls

The research model was subjected to control variables to account for any extraneous sources of variation in the firm's servitization processes. Firm age (FRMAG), firm size (FRMSZ), industry (IND), and slack resources (SLRES) were controlled for following Wales et al. (2013) and Abou-foul et al. (2021). The aforementioned controls were measured using objective data obtained from the OSIRIS database. The mean values of firm size and age over three years — from 2017 to 2019— were reported and transformed using the natural logarithm of a firm's number of employees and its age since incorporation. The 2-digit 2019 US standard industry classification (SIC) was used to control for industry membership effects; this variable was operationalized using dummy variables, with industrial and commercial machinery and computer equipment representing a reference group. Finally, slack resources were controlled and calculated using the current ratio. Research has found that higher levels of slack resources increase efficiency and the utilization of key resources and capabilities (Thornhill & Amit, 2003).

3.3 Psychometric properties of the measurement model

The two-step approach (Anderson and Gerbing, 1988) was followed to assess the psychometric properties of this study's measurement model. CFA was employed using AMOS 26 to assess the nomological validity of constructs, as well as the scale's reliability and validity. The study's measurement model achieved a good model fit and supported the unidimensional nature of the measurement items, with $\chi 2$=173 on 89 df, RMSEA=0.072, CFI=0.97, IFI=0.97, NFI=0.94, and TLI=0.95, exceeding the recommended values in the literature (Kline, 2015). Table 3 reports a summary of descriptive statistics and constructs intercorrelations which indicate good support for the direction of the study's hypothesized relationships. Cronbach's alpha was used to assess scale internal consistency reliability, and all scales achieved a satisfactory level of at least 0.70. All values of composite reliability (CR) were well above the benchmark level of 0.70, and the average variance extracted (AVE) values were all satisfactory, exceeding the threshold level of 0.50. These results are deemed satisfactory to establish convergent validity (Bagozzi & Yi, 1988).

Discriminant validity (see Appendix C) was assessed for the study's core constructs using the Heterotrait-Monotrait Ratio (HMTM), and all average correlations were below the cutoff value of 0.85, indicating sufficient evidence of discriminant validity (Henseler et al., 2015). We also tested the difference between $\chi 2$ in the constrained CFA model and the unconstrained model; the differences were found to be significant, providing more evidence of discriminant validity (Anderson and Gerbing, 1988). Furthermore, the study's scale items loaded significantly on their prospective construct. All standardized factor loadings are above 0.70 (except for two items at 0.65-0.64), and are all significant at $p < 0.001$ without any major cross-loading, establishing convergent validity (Anderson and Gerbing, 1988; Hair, 2010). Due to some inter-construct correlations being higher than the benchmark value of 0.60, a test of multicollinearity was performed which resulted in variance inflation factors (VIFs) ranging from 1.6-2.7, well below the recommended threshold of 5 (Hair, 2010). From this, we conclude that multicollinearity won't be a concern in our dataset.

{INSERT TABLE 3 HERE}

4 ANALYSIS AND RESULTS

Building on both CBSEM and fsQCA (e.g., Jahanmir et al., 2019; Torres et al., 2018), this study seeks to enhance this study's pragmatic implications and results. The implementation of variable-oriented techniques and case-oriented techniques in one analysis increases the granularity of the research results and the synergy in converging both methods to leverage causal complexity theory (Fiss, 2011; Misangyi et al., 2016).

4.1 Structural model results

Table 4 reports the results of the structural models following conventional CBSEM; two models have been tested. The first is the model of the direct effects of the four sub-dimensions of AICAP on servitization. This model's goodness-of-fit statistics indicate that the study's structural model fits the data, with $\chi 2$ = 24.801 (df = 22; p < 0.01), $\chi 2/df$ = 1.127, NFI= 0.962, CFI = 0.995, TLI = 0.993, RMSEA = 0.027, SRMR = 0.059. The path coefficient from AI for customer value proposition (AICVP) to servitization was significant, with β = 0.32; p < 0.001. The path coefficient from AI for key processes optimization (AIKPO) to servitization was significant, with β = 0.27; p < 0.001, while the path coefficients from AI for key resources optimization (AIKRO) and AI for societal good (AISGD) to servitization were significant, with β = 0.18; p < 0.001 and β = 0.30; p < 0.001, respectively. Consequently, H1a, H1b, H1c, and H1d are supported (see Figure 2), with a coefficient of determination R^2 =0.84 which explains 84% of the variance in the servitization construct.

{INSERT FIGURE 2 HERE}

The second model (see Figure 3) was developed to test the moderation effect of absorptive capacity (ACAP). Following the recommendations of Hayes et al. (2017) in testing interaction effects, the model achieved sufficient goodness-of-fit statistics, with $\chi 2$ = 20.310 (df = 18; p < 0.01), $\chi 2/df$ = 1.112, NFI= 0.970, CFI = 0.996, TLI = 0.994, RMSEA = 0.026, SRMR = 0.062. The path coefficient from AICAP to servitization was significant, with β = 0.83; p < 0.001. The moderation effect of ACAP) on AICAP and servitization was significant, with path coefficient $\beta = 0.08$; $p < 0.01$. Thus, the results give compelling support to H1 and H2. Meanwhile, the coefficient of determination $R^2 = 0.86$ explains 86% of the variance in the servitization construct. Finally, none of the control variables had any significant effect on servitization ($p > 0.05$), and no significant drop in R^2 (<1%) was reported when controls were not included in the tested models. Figure 4 graphically depicts the moderated relationship.

{INSERT FIGURE 3 HERE}
{INSERT FIGURE 4 HERE}
{INSERT TABLE 4 HERE}

4.2 Data and calibration

The data calibration phase is the first procedure in fsQCA and requires transforming the conventional variables into fuzzy-set scores, i.e., the input data for fsQCA analysis. Fuzzy-set scores reflect the degree of membership in the target set and range from 0 to 1. Thus, the four causal conditions —AI for customer value proposition, AI for key processes optimization, AI for key resources optimization, and AI for societal good — and the outcome servitization need to be calibrated.

In this study, the four causal conditions and the outcome are constructs measured with multiple items. To obtain fuzzy-set membership scores from the constructs, we needed to compute one value per construct to be used as input in fsQCA; to get this value we computed the mean of all the items that make up each construct.

Once we had transformed the constructs into single variables, we calibrated all the variables, in the same way, using the direct method of calibration (Ragin, 2009). In this process, the researcher needs to choose three breakpoints, or anchors, which define the level of membership in the fuzzy set for each case. Following Ragin's (2009) recommendations, we used fuzzy values of 0.95 for full membership, 0.50 for the crossover point, and 0.05 for full non-membership. To decide which values in our data set corresponded to the three anchor points, we used percentiles following the recommendations of Pappas and Woodside (2021). Our data did not follow a normal distribution but instead were skewed. Then we computed the 80th, 50th, and 20th percentiles of our measures and used these values as the thresholds for full membership, the crossover point, and non-membership, respectively, in fsQCA software (Pappas & Woodside, 2021).

In fsQCA, the cases that are exactly on 0.50 are dropped from the analysis because it represents the point of maximum ambiguity (Ragin, 2009). To overcome this, Fiss (2011) suggested adding a constant of 0.001 to the causal conditions below full membership scores of 1.

Once all variables were calibrated, we used fsQCA 2.0 free software to identify which causal conditions were necessary and sufficient for the outcome (SERV).

4.3 Analysis of necessary conditions

The analysis of necessary conditions examines whether any of the four causal conditions can be regarded as necessary for the outcome. Empirically, testing conditions for their necessity involves checking consistency and coverage thresholds. A condition can be considered necessary when its consistency and coverage values are above the 0.90 and 0.50 thresholds, respectively (Ragin, 2009).

Table 5 depicts the results of the analysis of necessary conditions and indicates that the consistency of the conditions was below 0.90 in all cases. Therefore, we find that none of the conditions in this study can be considered necessary for servitization.

{INSERT TABLE 5 HERE}

4.4 Analysis of sufficient conditions

According to Schneider and Wagemann (2010), sufficient conditions analysis includes three steps. The first is creating a truth table that includes the membership scores for all the possible configurations of causal conditions (Ragin, 2009). In our study, the truth table contains 16 rows $=2^k$, where k corresponds to the number of causal conditions. Second, the truth table must be simplified based on frequency and consistency thresholds. To reduce the truth table to relevant configurations, we set the cutoff points for the frequency at three observations as the minimum number of cases that need to be considered for a solution, capturing more than 80% of cases. The minimum consistency threshold was set at 0.80 (Fiss, 2011; Ragin, 2009). Finally, the last step is to obtain the solutions. Here, ‘solution’ refers to a set of conditions or configurations of conditions —which could be referred to as pathways— that constantly lead to high levels of servitization. These would constitute sufficient conditions. The fsQCA software was used to produce complex, parsimonious, and intermediate solutions. Following Ragin's (2009) recommendations, we report that the last one is the most interpretable. Table 6 provides the intermediate solution for the analysis of sufficient conditions.

{INSERT TABLE 6 HERE}

4.5 Formula of pathways

The three solutions we obtained were as follows (AICVP and AISGD) or (AICVP and AIKRO) or (AIKPO and AIKRO and AIKGD) => SERV.

Observing the results (see Table 6), the solution’s overall consistency for high servitization is 0.815 (> 0.740), and the overall solution coverage is 0.834 (> 0.450). Both indicators are above Ragin's (2009) recommended thresholds. We can see that there are three pathways to reach servitization, confirming equifinality (Fiss, 2011). The first configuration, Pathway 1, is the most empirically relevant (raw coverage = 0.670, unique coverage = 0.102, consistency = 0.873) and shows how a combination of AICVP and AISG is sufficient to lead to high levels of servitization. Pathway 2 (raw coverage = 0. 639, unique coverage = 0.070, consistency = 0.881) combines the presence of AICVP and AIKRO to lead to high levels of servitization.

Finally, pathway 3 shows a combination of three causal configurations, AIKPO, AIKRO, and AISG (raw coverage = 0. 591, unique coverage = 0.075, consistency = 0.899), to achieve a high level of servitization. The consistencies of every single pathway are above 0.75, indicating consistently sufficient routes to achieve servitization in all cases.

5 DISCUSSION

The possibility that AI capabilities, service innovation, and knowledge leveraging can lead to digital transformation success and social progress as well as solidify the basis for competitive advantage has emerged as paramount in recent years. Studies that examine the relationship between AI capabilities and servitization are still scarce and inconclusive, and businesses still struggle to capture the value of digital transformation due to bad measures and untargeted technology investment.

Prior research has mainly emphasized the implementation of new technologies and skills as a proxy for AI capability, without adherence to the micro-foundation of the business model in place (Mikalef & Gupta, 2021). Therefore, this study underscores the importance of looking beyond introducing specific technology and embedding AI capabilities in all interrelated components of a business model. Customer value propositions, resource and process optimization, and societal good were proposed as sub-dimensions of a firm's AI capabilities profile. This study's CBSEM found a significant positive effect of those sub-dimensions of AI capabilities on servitization, especially the effect of AI capabilities that enhance customer value propositions and societal good. These two AI capabilities help manufacturers advance their servitization processes and give confidence to management to proceed in the development of new servitized market offers. Our findings are also in line with other research findings (Akter et al., 2021; Burström et al., 2021). In line with prior literature AI applications and their related ML models are important to achieve resource efficiency and better sustainability performance, leading to personalized service provision and operational agility (Paiola & Gebauer, 2020; Sjödin et al., 2021). The findings also highlight the positive impact of AI capabilities that target resource mobilization on servitization, providing more evidence about the nature of this relationship, which is in line with previous studies that examined such relationships (e.g., Abou-foul et al., 2021). While our fsQCA did not reveal any necessary condition for servitization, this finding is in line with Davenport & Ronanki, (2018) and Park and Mithas, (2020), suggesting AI-enabled capabilities are not necessary for any configuration for service performance; a good explanation of such findings is that servitized market offering can be advanced building on cheap widely available technologies, matching the manufacturer level of servitization maturity in terms of market offerings. for instance. base services vs advanced services (Marcon et al., 2022; Raddats et al., 2022). However, it became evident that manufacturing firms require the presence of three out of four AI capability dimensions to consistently attain servitization, meaning that those capabilities are sufficient to achieve servitization and play an enabling role in some service innovation contexts. This finding, combined with the results of SEM, is also suggesting a symmetric view of causality that underpins servitization related to market heterogeneity (Parida et al., 2015).

Our fsQCA also highlighted that process and resource optimization combined with a contribution to societal good must be configured and presented to leverage collaboration between parties, servitization, and customer service provision, echoing the findings of Ferreira et al. (2020) and Toma et al. (2020). The net effect of AI on customer value propositions was significant and positive in the SEM analysis, while this finding echoes Payne et al. (2021) and Sjödin et al. (2021). However, the study offers a new perspective on AI for customer value propositions as our fsQCA failed to include it in all sufficient configurations to achieve servitization; despite achieving the highest path coefficient in our SEM analysis.

This finding could be attributed to a lack of customer data integration used to customize value propositions, which requires a certain degree of co-located data; this raises sensitive issues with prospective customers related to data governance, privacy, and data sovereignty, thus leading to trade-offs between privacy and ML models’ performance, which might impact servitization value propositions (Li et al., 2020; Rieke et al., 2020).

The study findings also offer some insights into the dynamics of organizational learning. We found some evidence that absorptive capacity strengthens the positive relationship between AI capabilities and servitization, giving great insight into such conditional dynamism. Societal good is shown to be important for advancing servitization. In our analysis, societal good appeared in two main servitization paths, indicating a substantial effect of this condition. However, the fsQCA at first glance might not support our SEM analysis about the importance of AI capabilities related to customer value propositions. Here, however, two important configurations included AICVP as a sufficient condition to reach servitization, balancing our regression analysis results. While prior research has advocated the assumption that the introduction of digitalization would enhance service provision (Abou-foul et al., 2021; Gebauer et al., 2021; Marcon et al., 2019), it might be true that it can foster efficiencies while failing to achieve competitive advantages, because other competing firms can adopt the same technologies, resulting in a so-called “Red Queen" competition (Barnett & Pontikes, 2008). Therefore, the results of our study provide additional insight into the role of data-driven AI capabilities in developing a firm's organic AI competencies, ecosystems, and co-specialized resources to leverage the firm’s dynamic capabilities (Mikalef et al., 2021).

5.1 Theoretical implications

This paper offers several important theoretical contributions. First, it integrates studies on AI capabilities, dynamic capabilities, and servitization. It develops and empirically tests a theoretical model to address those relationships in a manufacturing context. The study results help in addressing the controversial interdependencies and the value of AI investment for servitization (Garcia Martin et al., 2019; Leone et al., 2021; Libai et al., 2020; Waltersmann et al., 2021). The results demonstrate that higher-order capabilities such as those related to AI have a direct impact on firm servitization, and the strength of this relationship is contingent on the company’s absorptive capacity. Furthermore, drawing on the emergent literature on complexity and set theory (Anderson, 1999; Ragin, 2009; Woodside, 2014), this study reveals the mechanism and the differences in configurations in which servitization can be achieved. Second, this study makes a direct contribution to DCT by extending our understanding of the micro-foundation of dynamic capabilities and how they can be translated into a manufacturing context by developing firm-specific methodological individualism (Felin & Hesterly, 2007) in the form of unique cognitive technologies and resource orchestration to leverage both knowledge internalization in data infusion and service innovation (Barrett et al., 2015; Neirotti et al., 2021). Our results also emphasize the objectives of AI applications within the firm business model to achieve servitization. Consistent with a growing body of research, the current research classification of AI capabilities and its integration of the dynamic capabilities framework highlights the role of AI applications in advancing customers' value proposition, which requires sensing capabilities for opportunities assessment and identification. It also complements DCT in which AI application for resources mobilization can advance a firm's seizing capabilities and its complementary assets. Our model also pinpoints the transformational capabilities embedded within AI applications targeting sustainability issues emphasizing the strategic continual renewal through business model innovation and knowledge absorption (Bag et al., 2021; Scuotto et al., 2022; Sjödin et al., 2021). Our study also unearths a set of factors that shows the mechanism in which a firm's AI capabilities can be advanced to advance servitization and we also opened the discussion on the optimal configuration of AI applications to tackle the complex configurations of service innovation in manufacturing firms (Payne et al., 2021).

Third, this research offers and empirically validates a multidimensional scale to assess AI capabilities (Mikalef & Gupta, 2021). Consistent with the dynamic capabilities perspective, this paper advances the AI capabilities conceptualization domain more comprehensively, in which findings highlight both the critical higher-order capabilities achieved by executing applied intelligence and the integration of AI capacities in transforming and innovating manufacturing business models that emphasize servitization (Kamp et al., 2017). Finally, the novel scale was tested across several industrial classifications, helping to improve its validity and providing a desirable level of generalizability.

5.2 Managerial implications

This paper provides a fine-grained perspective to managers engaging in developing AI capabilities and servitization. First, manufacturing firms may consider their knowledge-intensive, higher-order capabilities such as AI capabilities and absorptive capacity, to better sense customer preferences, shape internal processes and resources to integrate customers and deliver new value propositions, and seize opportunities by embedding AI capabilities in business models to better fit turbulent environments and technological advancement. Furthermore, AI advancement can also help managers in increasing service agility and responsiveness, which require companies to fine-tune internal processes, functional capabilities, structures, and, ultimately, strategy (Felin & Powell, 2016). AI capabilities can also help companies disrupt key revenue streams of incumbents in the ecosystem, especially in advancing direct-to-customer functions that mainly service the company's customer base (Sjödin et al., 2020a).

Second, the results of this study highlight that decision-makers should not focus only on internal optimization of the manufacturing process, but should instead look outward and increase their machine learning capabilities, big data analytics, deep learning, and robotics to deliver services that benefit social causes. Managers must also treat data as a strategic resource powering prescriptive key performance indicator (KPIs) that define, develop, and refine servitization (Payne et al., 2021). On a similar note, managers should increase their investment in AI research and commercialization, especially in customer-facing AI, to enhance predictive customer intelligence that directly enhances customers' lifetime value. This requires coordination efforts between parties to create better integration and better machine learning models, meaning that the success of AI implementation is dependent on fine-tuned ML models that feed on data. Managers also should understand that acquiring data requires a trusting partnership between players in the ecosystem. Parallel to this, manufacturers should also focus on services with clear positive societal impacts which accelerate and cultivate decarbonization initiatives, and the mandatory consideration of data governance issues. Third, managers should fully understand the progressive nature of absorptive capacity and its cross-functional properties. Therefore, they have to integrate and assimilate knowledge acquired internally and externally in the development process of organic AI applications. In this context, AI capabilities can be utilized and further developed to enhance raw data exploration, ML model architecture and prototyping, application platforms, data security, and analytics (Lehrer et al., 2018).

Furthermore, building on the study, theoretical model managers should focus their efforts on enhancing AI applications that highly drive servitization; this can be achieved by advancing customer value propositions and data integration techniques, for better market offerings that are built on collecting valuable and granular customer insight. Of equal importance, managers should focus their AI investment on enhancing internal processes that enhance effectiveness and efficiency. AI for key resources optimization can help in managing supply-chain transportation bottlenecks and enables prescriptive insights into workloads and risk management. Managers also should view AI capabilities as a source of competitive advantage in advancing stronger energy policies. Manufacturers also need to prioritize the investment in AI algorithms that enhance value proposition that serves sustainability causes, especially in industries facing a tough time immigrating to a new greener solution amid the current energy crisis. Therefore, managers can advance their servitized market offerings by providing services that reduce clients’ energy emissions, improve workplace safety, and extend product lifetime and overall environmental performance. Finally, managers should proactively pursue the current and future opportunities rises from the assistive role of AI, by developing more powerful cognitive technologies, targeting process and human augmentation, service provision and governance, this can be achieved by enhancing the quality of information and the use of expert systems that provide a platform for business adaptation and ultimately evolution (Dwivedi et al., 2021).

6 LIMITATIONS AND CONCLUSION

The findings of this research are instructive in many ways. However, they come with some limitations that can be resolved in future research. First, while using dynamic capabilities as a theoretical lens is justified, we address its scope and conditions (Winter, 2003). Therefore, it is recommended to stress test our findings using different theoretical lenses, especially for those companies which operate in ecosystems built on process outsourcing to achieve operational flexibility, which might impede the internal development of AI capabilities. Furthermore, a good avenue of future research could be to incorporate organizations' AI maturity levels when collecting samples. Further empirical work should also focus on AI governance, technical diligence, affordability, and industry-level capabilities (Thuraisingham, 2020) to provide a more parsimonious explanation of servitization. Second, from a methodological point of view, we recommend testing the proposed model in different settings using different datasets to provide more empirical evidence of our model's predictive power using longitudinal data. Further, we are still in the first stages of understanding AI developments and their impact on business contexts (Mikalef & Gupta, 2021). Therefore, our AI capability construct is not a one size fits all panacea to measure manufacturing firms' AI initiatives, and its scale is by no means exhaustive. We highly recommend embedding AICAP and its four dimensions into a nomological network that has causal antecedents to better test the concept and reduce any artificial entities that are generated by statistics. Researchers should treat this scale with caution when applying it in different settings and address any other dimensions deemed necessary to any contingent aspects. Third, it has been a temptation from our side to eliminate some causal biases attributed to model specification and sample heterogeneity which might confound the analysis; therefore, we opt to support our work by using set theory applications by examining the combinatorial effect of AI capabilities on servitization. Therefore, it is of great importance that researchers revalidate our assumptions and configurations to further inspect the role of customer value propositions in service innovation to resolve any conflicting empirical findings. All in all, the positive effects of AI capabilities and servitization in creating business and societal value are still to be established in the literature (Raddats et al., 2019; Vinuesa et al., 2020). Our study finds that AI capabilities positively impact servitization, while higher absorptive capacity is linked to a stronger impact of AI capabilities on servitization. Our study also concludes that, *ceteris paribus*, AI capabilities designed for leveraging societal good, resource optimization, and process optimization are sufficient to lead to servitization. Finally, this research is inclined to inspire additional scholarly inquiry linking AI capabilities to moderating conditions and nonlinear service innovation outcomes.

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Table 1. Definitions of the constructs.

Construct	Definition
Servitization (Kowalkowski et al., 2017a)	The transformational processes whereby a company shifts from a product-centric to a service-centric business model and logic.
AI Capabilities (Mikalef & Gupta, 2021)	A firm’s ability to select, orchestrate, and leverage its AI-specific resources, in order to identify, interpret, make inferences, and learn from data to achieve predetermined organizational and societal goals.
Absorptive Capacity (Zahra & George, 2002)	A set of organizational routines and processes by which firms acquire, assimilate, transform, and exploit knowledge to produce a dynamic organizational capability.

Table 2. Sample characteristics.

	% (N = 185)
Industry (US 2 digits SIC code)	
(13) Oil and gas extraction	10
(29) Petroleum refining and related industries	14
(35) Industrial and commercial machinery and computer equipment	24
(36) Electronic and other electrical equipment and components	22
(37) Transportation equipment	6
(38) Measuring, analyzing, and controlling instruments	19
(49) Electric, gas, and sanitary services	5
Company Size	
1-250 employee	12
250+ employee	88
Respondent position	
Service Manager	27
Head of IT	25
Chief Information/ Technology Officer	21
Chief Operations Officer	11
Other (Lead data scientist, IT Project Manager, Marketing Manager, etc.)	16
IT and/or service experience	
Less than one year	14
1- 2 years	21
3-4 years	27
More than 4 years	38

Table 3. Summary of descriptive statistics, latent variables inter-correlations for first-order constructs, and psychometric characteristics.

		Mean	**SD**	**CR**	**AVE**	1	2	3	4	5	6	7	8	9	10
1	AICVP	3.6	1	0.88	0.65	(0.82)									
2	AIKPO	4	1	0.91	0.63	0.52**	(0.88)								
3	AIKRO	4.2	0.98	0.85	0.59	0.56**	0.68**	(0.78)							
4	AISGD	3.9	1	0.88	0.72	0.52**	0.59**	0.70**	(0.80)						
5	ACAP	3.9	1	0.90	0.72	0.65**	0.76**	0.75**	0.71**	(0.90)					
6	SERV	3.8	1	0.92	0.55	0.72**	0.74**	0.75**	0.75**	0.63**	(0.91)				
7	FRMSZ (LN)[a]	10.7	1	-	-	0.06	-0.02	-0.13	-0.04	-0.00	-0.06	(n/a)			
8	SLRES	1.5	0.7	-	-	-0.15*	-0.10	-0.06	-0.16*	-0.15*	-0.13	-0.13	(n/a)		
9	FRMAG (LN)[a]	2.9	3.4	-	-	-0.05	-0.03	-0.04	-0.13	-0.03	-0.08	-0.02	0.11	(n/a)	
10	IND	34	10	-	-	-0.02	-0.03	-0.06	-0.09	-0.09	-0.09	-0.09	-0.05	0.01	(n/a)

Notes: N = 185
SD—standard deviation.
Cronbach's alpha (α) presented along diagonals, CR—composite reliability, AVE—average variance extracted.
[a] logarithmically transformed to reduce skewness.
(n/a) Not applicable.
**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Table 4. Test results for the structural models.

Parameter [a]	Direct effects model [b]	Interactive model [c]	Result
Hypothesized paths			
AICAP→SERV (**H1**)	-	0.83^{***}(17.24)	●
AICAP×ACAP →SERV (**H2**)	-	0.08^{**}(3.30)	●
Control variables			
IND→ SERV	-0.05^{ns} (1.38)	-0.04^{ns} (1.43)	
FIRMSZ→ SERV	0.01^{ns} (0.06)	-0.04^{ns} (1.68)	
FIRMAG→ SERV	0.01^{ns} (0.19)	-0.03^{ns} (0.95)	
SLRES→ SERV	-0.04^{ns} (1.24)	-0.01^{ns} (0.33)	
Measurement model and first-order factors [d]			
AICVP →SERV(**H1a**)	0.32^{***} (7.5)	-	●
AIKPO →SERV(**H1b**)	0.27^{***}(6.4)	-	●
AIRKRO → SERV(**H1c**)	0.18^{***}(3.8)	-	●
AISGD →SERV (**H1d**)	0.30^{***}(5.6)	-	●
Goodness-of-fit statistics			
$\chi 2$	$=24.801^{***}$	$=20.310^{***}$	
df	=22	= 18	
NFI	=0.962	=0.970	
CFI	=0.995	=0.996	
TLI	=0.993	=0.994	
RMSEA	=0.027	=0.026	
SRMR	=0.059	=0.062	
R^2	= 0.840	=0.866	
N	185	185	

[a] Estimates are standardized with *t*-values shown in parentheses.
[b] Includes only the direct effect of the decomposition of AI capabilities on servitization.
[c] Includes only the moderating effect of absorptive capacity on the second-order AI capabilities construct and servitization.
[d] All the item loadings for the first-order factors were significant at $p < 0.001$.
[ns] *p*-value is not significant.
● Indicates the full degree of confirmation.
Chi-square ($\chi 2$); Degree of Freedom (df); Normed Fit Index (NFI); Goodness of Fit Index (GFI); Comparative Fit Index (CFI); Tucker-Lewis index (TLI); Root Mean Square Error Approximation (RMSEA); Standardized Root Mean Squared Residual (SRMR); R^2 coefficient of determinant.
$^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table 5. Analysis of necessary conditions.

Conditions tested	**Consistency**	**Coverage**
AICVP	0.790	0.755
~AICVP	0.349	0.332
AIKPO	0.826	0.787
~AIKPO	0.358	0.341
AIKRO	0.794	0.749
~AIKRO	0.369	0.355
AISGD	0.797	0.745
~AISGD	0.362	0.351

Outcome variable: SERV
"~" represents the absence of a condition.

Table 6. Sufficient configurations of conditions for servitization.

The configurations leading SERV	Raw coverage	Unique coverage	Consistency
AICVP * AISGD	0.670	0.102	0.873
AICVP * AIKRO	0.639	0.070	0.881
AIKPO *AIKRO * AISGD	0.591	0.075	0.899
Solution coverage: 0.815			
Solution consistency: 0.834			

Note: AICVP = AI for customer value proposition; AIKPO = AI for key processes optimization; AIKRO = AI for key resources optimization; AISGD = AI for societal good

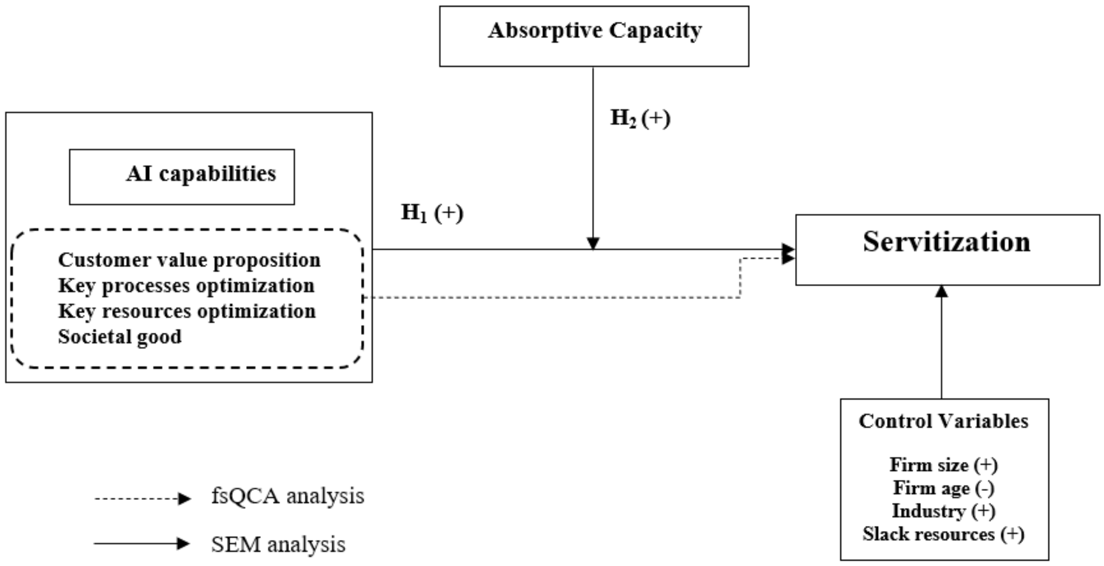


Figure 1: Research Model.

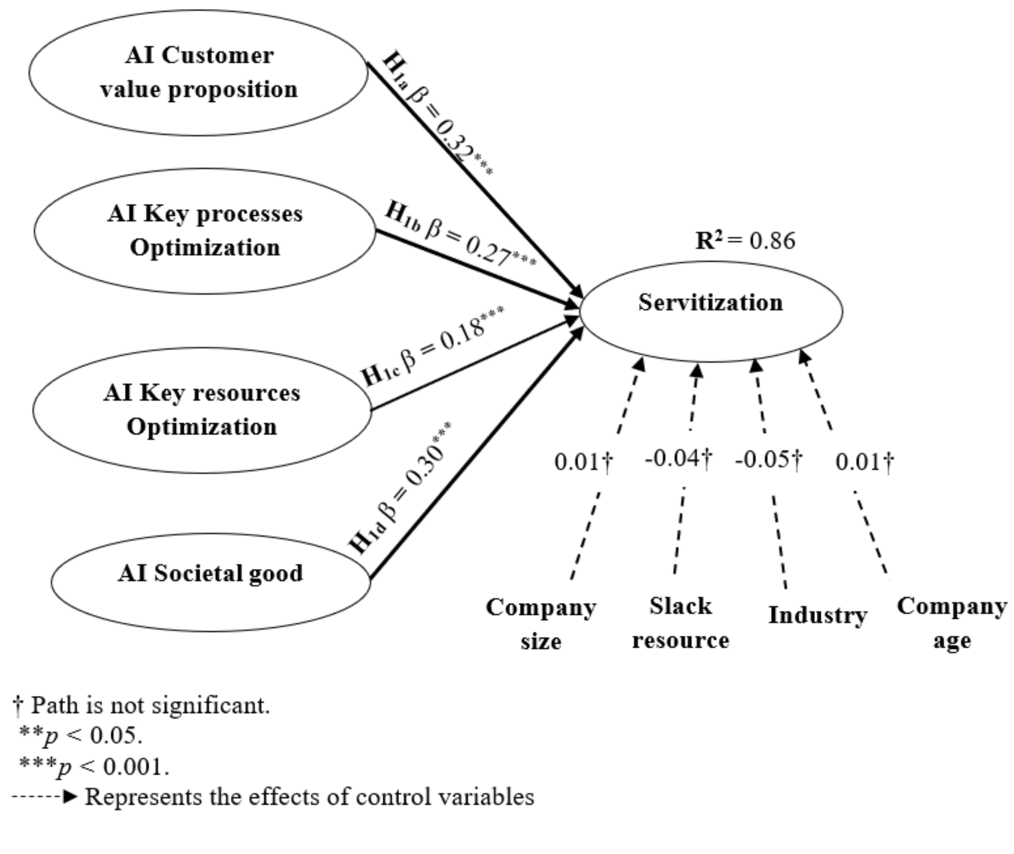
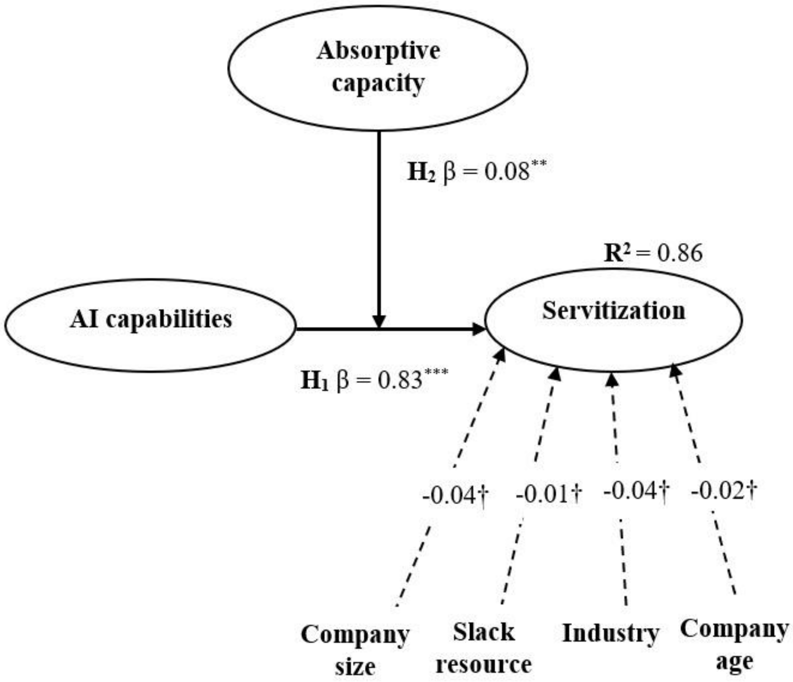


Figure 2: The results of the direct effects model.



† Path is not significant.
$^{**}p < 0.05$.
$^{***}p < 0.001$.
-------► Represents the effects of control variables

Figure 3: The results of the interactive effect model.

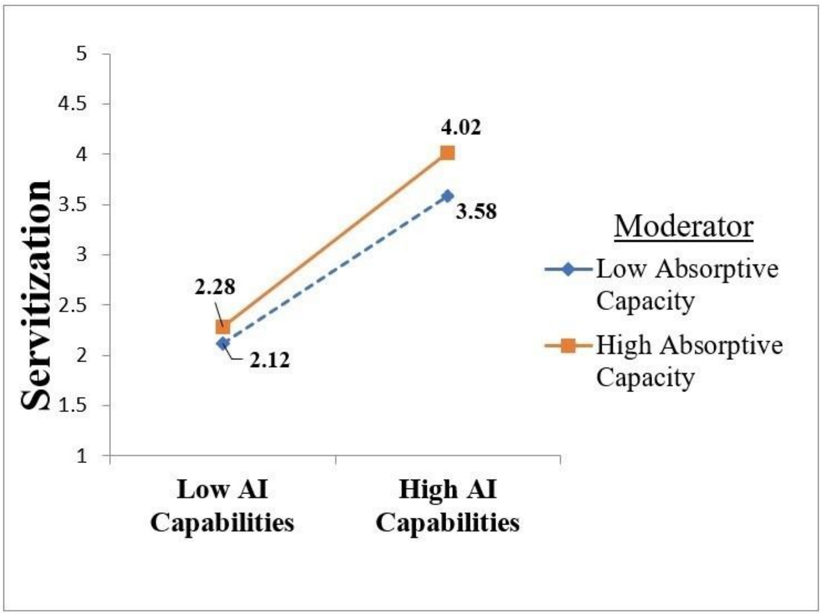


Figure 4: Moderating effect of absorptive capacity.

Appendix A

Constructs and measurement items. [a]

Variables	Standardized factor loading
AI capabilities [b]	
AI customer value proposition	
Our company is collecting after-sales insights and uses AI to personalize the customer experience and ensure our customers' success.	**0.82*****
Our specialized data science team uses tools to calculate our customer's optimal warranty cost and duration.	**0.78*****
Our company is using machine learning models in pricing and quoting optimization.	**0.86*****
Our company collects and analyses embedded sensor data to provide our customers with predictive maintenance, and operation optimization services.	**0.76*****
AI key processes optimization	
Our company is using advanced data science in demand forecasting and stocking.	**0.77*****
Our company is making a strategic data acquisition to fulfill customers' orders on time.	**0.73*****
Our company integrates AI conversational agents' capabilities such as chatbots in our next-generation CRM.	**0.80*****
Our company uses advanced robotics and predictive maintenance in our internal operations applications.	**0.81*****
Our company uses intelligence capabilities such as machine vision and edge analytics in enhancing yield optimization.	**0.80*****
Our company uses AI data mining capabilities and big data systems to enhance our product innovation process and bill of material (BOM).	**0.84*****
AI key resources optimization	
Our company applies analytics to unified data warehouses to optimize our suppliers' network.	**0.78*****
Our company uses AI applications to optimize our labor workforce.	**0.80*****
Our company uses advanced analytics to optimize our network's resources, ensure cybersecurity and safeguard our data.	**0.72*****
Our company uses AI applications to identify our lowest-cost provider.	**0.76*****
AI societal good	
Our company trains AI assistants to enhance workplace safety.	**0.87*****
Our company uses applied AI such as deep reinforcement learning to cut our operation's energy consumption, emission, waste, and equity.	**0.90*****
Our company uses data analytics and benchmarks to provide green solutions to our customers that tackle the most prominent societal challenges such as decarbonization.	**0.77*****
Servitization [c]	

Top management service orientation	
Our senior leaders are rarely aligned around the strategic importance of servitization transformation. [r]	**0.76*****
Our senior leaders are actively promoting a vision of the future that involves servitized offerings.	**0.85*****
We regularly review with the top team our progress on servitization transformation.	**0.86*****
Mobilization of resources	
Our employees understand the benefits of servitization change.	**0.72*****
Our firm is investing in the necessary skills and capabilities to provide servitized offerings.	**0.74*****
Our business cases and key performance indicators are linked to our roadmap.	**0.81*****
Market offering	
Our firm has taken over some of our customer's business processes.	**0.75*****
Our firm has taken over the operational functions of our products in customers' businesses.	**0.79*****
Our service contracts related to our products are designed to share 'risk and reward' with our customers, so our customers pay for the product's capabilities, outcomes, and results.	**0.82*****
Absorptive capacity [d]	
The search for relevant information concerning our industry is everyday business in our company.	**0.79*****
Our management demands periodic cross-departmental meetings to discuss new developments, problems, and achievements.	**0.87*****
In our company there is a quick information flow, e.g., if a business unit obtains important information, it communicates this information promptly to all other business units or departments.	**0.65*****
Our employees successfully link existing knowledge with new insights.	**0.83*****
Our company rarely reconsiders technologies and adapts them according to new knowledge. [r]	**0.64*****
Our company lacks the ability to work more effectively by adopting new technologies. [r]	**0.80*****
Control variables [e]	
Firm size (LN employee)	-
Firm age (Since incorporation)	-
Industry classification (2 digits US-SIC code)	-
Slack resources (Current ratio)	-

[a] All items were measured using a 5-point Likert scale with 1 = Strongly disagree, 2 = Disagree, 3 = Neither agree nor disagree, 4 = Agree, and 5 = Strongly agree.
[b] New items developed by authors.
[c] Adopted from (Abou-foul et al., 2021).
[d] Adopted from (Flatten et al., 2011).
[e] Objective measures.
[r] Item reversed.
****p* < 0.001.

Appendix B

Second-order factor results.

Model	Normed $\chi 2$	TLI	NFI	CFI	RMSEA
Recommended Value [a]	≤2	>0.90	>0.90	>0.90	<0.08
AI Capabilities					
Model 1 (one-factor model)	6.468	0.801	0.808	0.842	0.139
Model 2 (four uncorrelated factors)	5.362	0.937	0.914	0.922	0.170
Model 3 (four correlated factors)	2.512	0.930	0.924	0.956	0.081
Model 4 (one second-order factor)	1.944	0.947	0.932	0.965	0.062

[a] Based on (Kline, 2015).

Normed $\chi 2 = \chi 2/df$ (relative chi-square); TLI—Tucker Lewis index; NFI—normed fit index; CFI—comparative fit index; RMSEA—root mean square error aggregate.

Appendix C

Heterotrait-Monotrait Ratio (HMTM).

		(1)	(2)	(3)	(4)	(5)	(6)
(1)	ACAP						
(2)	AIKPO	0.653					
(3)	AIKRO	0.700	0.772				
(4)	SERV	0.799	0.818	0.830			
(5)	AISGD	0.851	0.688	0.746	0.729		
(6)	AICVP	0.584	0.596	0.645	0.821	0.626	