Deusto
Universidad de Deusto
Deustuko Unibertsitatea
University of Deusto

Exploring Servitization Across Time: From Past Evolution to Future Innovations

PhD programme in Business and territorial competitiveness, Innovation and Sustainability

Deusto Business School

Bilbao, January 2025

Doctoral Candidate:

Juan Carlos Monroy Osorio

Juan Carlos Monroy Osorio
Firmado digitalmente por Juan Carlos Monroy Osorio
Fecha: 2025.01.28 14:36:54 -05'00'

Doctoral Co-Supervisor:

Marco Opazo Basáez
Firmado digitalmente por Marco Opazo Basáez
Nombre de reconocimiento (DN): cn=Marco Opazo Basáez, o=Universidad de Deusto, ou=Deusto Business School, email=marco.opazo@deusto.es, c=ES
Fecha: 2025.02.22 16:09:43 +01'00'

Prof. PhD. Marco Opazo-Basáez

Doctoral Co-Supervisor:

Ferran Vendrell-Herrero
Digitally signed by Ferran Vendrell-Herrero
Date: 2025.01.28 21:06:32 Z

Prof. PhD. Ferrán Vendrell-Herrero

Abstract

This study explores the evolution of servitization, focusing on its transition from product-centric models to service-oriented strategies enabled by digital technologies. Servitization emphasizes value co-creation through services, moving beyond traditional goods-based frameworks. By integrating tools such as Artificial Intelligence (AI), the Internet of Things (IoT), and advanced analytics, firms can improve operational efficiency, customer engagement, and sustainability. Using Organizational Information Processing Theory (OIPT), the research examines AI's role in mediating the relationship between Digital Service Innovation (DSI) and business performance, highlighting the use of by-product data to enhance decision-making. Empirical evidence from Spanish manufacturing firms distinguishes between digitally enabled strategies that optimize existing processes and digital-first strategies that embed sustainability into operational design. These approaches demonstrate the potential for addressing challenges such as resource scarcity and emissions reduction while aligning with sustainability objectives. The findings contribute to servitization theory by connecting it to digital transformation and sustainability, offering practical frameworks for integrating ethical and responsible practices. This study provides a foundation for understanding how servitization and digital technologies can work together to improve business performance and support long-term environmental goals. It identifies future research opportunities, including the ethical implications of AI and the broader application of digital frameworks across industries and contexts. By linking historical developments with contemporary innovations, this research outlines how firms can integrate servitization strategies with digital tools to meet evolving performance and sustainability demands.

Keywords: Servitization; Digital servitization: Digital Service Innovation; Sustainability; Strategy

Acknowledgments:

To all those who, with their words of encouragement, their thoughtful reviews of every attempt I made, their advice, and their teachings, helped me move forward on this journey. To my supervisors, Pro. Marco and Prof. Ferrán, whose guidance and encourage has been invaluable and I will always cherish as enduring lessons. To my doctoral colleagues, whose kind words, advice and help I will forever treasure, and for all the moments that made this journey unforgettable. To my special ones—family and friends in all my homes and places—thank you for your unwavering commitment, companionship, kindness, and care. To the places that became part of my journey, the bars and walks, thank you for the open door and the comfy chair. To the cities and countries that welcomed me, allowing me to study, grow, and thrive. To the Universities, may the time invested prove brief compared to the opportunities and challenges that lie ahead. To myself, for reaching this point through effort and joy.

To all of you, thank you. May all the effort I have made, and will continue to make, repay the effort you have made for me. You know who you are, and you hold a place in my life.

Cheers.

Table of Contents

1. Introduction: From Mass Consumption to Servitization: Shaping Business Strategy and Sustainability Practices *9*

1.1 Servitization in the Modern Era: Transforming Industries and Consumption Patterns 9

1.2 From Servitization to Digital Service Innovation: Strategies Oriented to Services .. 12

1.3 Servitization Theory and the Efforts Toward a Future, Sustainable World 15

2. Research question and objective of the thesis compendium *19*

3. Methodology implemented in the compendium *25*

3.1 Methods 25

3.2 Sample 26

3.3 Variables 26

Chapter 4. Compendium Article 1 .... *29*

Chapter 5, Compendium article 2 .... *31*

Chapter 6, Compendium article 3 .... *33*

Chapter 7: Discussion and Conclusions *34*

7.1 Synthesis of Key Findings from the Articles 35

7.2 Comparative Analysis Across the Articles 36

7.3 Reflection on Theoretical and Practical Implications of the Research 39

7.4 Suggestions for Future Research Directions 41

8. References. *42*

List of Tables:

Table 1: Servitization seen as a progression from historical foundations to contemporary innovations and future sustainability efforts *23*

Table 2: Contributions from the three papers *42*

List of Figures:

Figure 1: Conceptual network graph with correlation of concepts in papers conclusions. 39

Preface

Academic pursuits have always been a cornerstone in my family. My father, a professor of Engineering, often took us to the university during vacations, immersing us in an academic atmosphere where curiosity and learning thrived. These formative experiences shaped my early love for education and research. Equally, my mother always tells us the important were the values of rigor, perseverance, and commitment instilled by my family. These principles guided me as I taught my first class at just 21, a role that marked the beginning of my academic journey and a profound sense of vocation. After a couple of years, in 2011, I completed a master's degree in human-computer interaction (HCI), which became my initial encounter with user and consumer research. This experience broadened my understanding of how technology shapes human experiences. My formal academic career began in 2015 when I joined EAFIT University, one of Latin America's most esteemed business schools, as an assistant professor of digital marketing.

My background in engineering instilled a methodological approach to research, while my work in marketing allowed me to focus on understanding how manufacturing firms use services to connect with consumers, generating value and contributing to sustainability. This research interest deepened through collaborations with esteemed scholars such as Professor Marco Opazo from the University of Deusto and Professor Ferrán Vendrell from the University of Edinburgh. Their work inspired me to pursue doctoral studies at the University of Deusto, a region with a long tradition of industrial transformation through services. The transition from professor to student might seem counterintuitive, but it was one of the most enriching phases of my academic journey. It offered me a fresh perspective, where listening, questioning, and reflecting became essential tools for learning and growth. This shift taught me the value of unexpected outcomes and the necessity of adapting research questions in response to emerging insights. Originally focused on the impact of servitization on end consumers, my inquiry evolved into a historical examination of servitization and its influence on the sustainability strategies of modern organizations.

This thesis explores the origins of servitization and its role in contemporary technological discourse, particularly how firms integrating services with artificial intelligence components can achieve sustainable business performance. The final chapters highlight the transformative potential of services for long-term sustainability goals. Alongside this research, two additional publications emerged: *Evaluating the Effect* *of Green Technological Innovations on Organizational and Environmental Performance: A Treble Innovation Approach*, published in *Technovation* (Opazo-Basáez et al., 2024), and *Advance Servitization's Role on Managerial Paradoxical Tensions in Manufacturing Firms*, forthcoming in the *International Journal of Business Environment*. These works extend the discussion on sustainability in manufacturing by examining how servitization reconciles knowledge paradoxes and supports strategic growth.

The following thesis represents the culmination of years of research, collaboration, and personal growth. It is a testament to the enduring passion for academia nurtured in my youth and refined throughout my professional and doctoral journey. Thank you for taking the time to engage with this work.

CHAPTER 1. INTRODUCTION

1. Introduction: From Mass Consumption to Servitization: Shaping Business Strategy and Sustainability Practices

1.1 Servitization in the Modern Era: Transforming Industries and Consumption Patterns

The evolution of economic systems over the past two centuries has profoundly influenced contemporary approaches to sustainability and business strategy. Economic models have transitioned from agrarian economies focused on subsistence to industrial systems characterized by mass production and, more recently, service-oriented frameworks that prioritize value creation (Brax, 2005). The Industrial Revolution marked a defining moment in this trajectory, introducing mechanized production methods prioritizing efficiency, scalability, and the widespread distribution of goods. This shift enabled societies to move beyond localized, resource-dependent economies, giving rise to global markets and consumer cultures centered on ownership and material wealth (Savva et al., 2011). However, the rapid industrialization underpinning this growth revealed critical limitations, including environmental degradation, resource depletion, and socio-economic inequalities (B.Holbrook et al., 2002). These challenges underscore the pressing need for innovative strategies to reconcile economic growth with ecological and social imperatives. Historically, the industrial focus on maximizing production overlooked the broader impacts of such practices, often externalizing costs onto the environment and communities (Stole, 2007). This historical context serves as a foundation for understanding the necessity of frameworks that address these inefficiencies, paving the way for approaches that align profitability with sustainability. Lessons from the industrial era inform modern strategies by highlighting the importance of moving beyond purely goods-centered systems, offering insights into the potential of integrative models that balance economic objectives with environmental resilience (Petrulaitiene et al., 2018).

The conceptual framework of servitization emerges as a transformative response to these historical limitations, representing a significant shift in economic thought. Servitization challenges the traditional goods-centered model by emphasizing value co-creation through services, positioning them as integral to economic exchange (Raddats et al., 2019; Spring & Araujo, 2013). Central to this transformation is the service-dominant logic (S-D logic) articulated by Vargo and Lusch, which reconceptualizes the foundational principles of economic activity. Initially grounded in goods-focused and manufacturing-based practices, marketing evolved during the Industrial Revolution to address the production and distribution of tangible goods (Vargo & Lusch, 2008). This perspective dominated economic exchange for much of the twentieth century, framing goods as the primary unit of value. However, over time, businesses expanded its scope to include services, giving rise to the subdiscipline of service innovation (Lusch et al., 2006). Despite this broadening perspective, service delivery and innovation retained its roots in goods-based paradigms, characterizing services through intangibility, inseparability, heterogeneity, and perishability (Calabretta et al., 2016). While useful within a manufacturing framework, these distinctions must be revised to capture service interactions nuanced and relational nature. Vargo and Lusch propose an alternative perspective, suggesting that service, defined as the application of competencies for the benefit of others, constitutes the foundational basis of all economic exchange (Vargo & Akaka, 2009). Goods, in this view, are merely vehicles for delivering services. This shift in perspective broadens the scope of marketing and strategic thinking, aligning them with contemporary demands for flexibility, customization, and sustainability. By prioritizing relationships and interactions over transactions, the S-D logic provides a comprehensive framework for addressing the dual challenges of economic growth and environmental stewardship (Lusch & Vargo, 2014). It underscores the importance of co-creating value with stakeholders, offering insights into how businesses can adapt to evolving societal needs while maintaining competitive advantage (Garcia Martin et al., 2019; Opazo-Basaez et al., 2020).

Building on this theoretical foundation, servitization has become a significant feature of the modern economy, reflecting the integration of services into traditionally product-focused industries (Vendrell-Herrero et al., 2017). The transition from mass consumption to servitization signifies a realignment of business models, moving from goods production to service-oriented strategies prioritizing customer engagement and value creation. Recent research highlights how this transition is driven by technological advancements, changing consumer preferences, and an increasing emphasis on sustainability (Monroy-Osorio et al., 2023). Servitization leverages innovations such as the Internet of Things (IoT), artificial intelligence (AI), and predictive analytics to enhance service delivery, optimize resource use, and foster deeper customer relationships. These technologies enable businesses to shift from transactional relationships to models emphasizing long-term value creation, aligning their strategies with broader societal and environmental goals (Baines & Lightfoot, 2013; Khanra et al., 2021). Industries such as manufacturing, automotive, and healthcare exemplify this shift, adopting servitization to offer equipment leasing, predictive maintenance, and performance monitoring solutions. For instance, manufacturing firms now integrate IoT sensors into their products, allowing them to monitor usage patterns and predict maintenance needs, extending product life cycles and enhancing customer satisfaction (Paslauski et al., 2016).

Similarly, automotive companies have introduced subscription-based models that provide consumers access to vehicles and related services without needing ownership. These approaches enhance customer experiences and align with sustainability objectives by reducing waste and promoting circular economy principles (Parker & Van Alstyne, 2018). By integrating services into their core offerings, firms address global challenges such as resource scarcity, waste management, and carbon emissions. Consequently, servitization decouples economic growth from resource consumption, fostering innovation and resilience in a rapidly changing marketplace (Matyushok et al., 2021).

The progression from mass consumption to servitization reflects a broader evolution in economic paradigms, linking historical practices with modern innovations that address contemporary challenges. This transformation highlights the potential of servitization to redefine industries, emphasizing value co-creation to achieve competitive advantage and sustainability (Monroy-Osorio et al., 2023). Moreover, integrating service-oriented strategies into traditional business models demonstrates the adaptability of servitization to diverse sectors and contexts, reinforcing its relevance in the global economy. As servitization continues to shape industry practices, it also lays the groundwork for further advancements, particularly in digital service innovation (Vendrell-Herrero & Wilson, 2017). Digital technologies such as AI, IoT, and advanced data analytics build on the principles of servitization, providing tools to enhance service efficiency, customer engagement, and operational sustainability. This transition transforms how businesses interact with their customers and reimagines technology's role in addressing global challenges (Bustinza et al., 2018). Integrating digital service innovation represents the next phase in this evolutionary trajectory. It offers new pathways for businesses to align their strategies with sustainability imperatives while maintaining competitiveness in an increasingly dynamic global economy. This progression underscores the interconnectedness of historical developments, theoretical frameworks, and practical applications, illustrating the ongoing relevance of servitization as a cornerstone of modern business strategy (Opazo-Basáez et al., 2018; Vendrell-Herrero et al., 2018).

1.2 From Servitization to Digital Service Innovation: Strategies Oriented to Services

In the present landmark of manufacturing companies' strategies, technology has become an important base-structure. By integrating advanced technologies, including artificial intelligence (AI), the Internet of Things (IoT), and digital sensors, it transforms service offerings in modern business environments (Shankar, 2018; Soto Setzke et al., 2023). Such technologies facilitate the collection, analysis, and utilization of substantial quantities of contextual and operational data, significantly enhancing service personalization, efficiency, and reliability. AI has emerged as a cornerstone of this transformation, enabling the processing of large datasets to identify patterns, predict customer behaviors, and support real-time decision-making (Huang & Rust, 2018). IoT and sensors complement AI by generating continuous data streams from interconnected devices, offering valuable insights into operational conditions, customer usage, and product performance. For instance, predictive maintenance models utilize IoT sensor data to forecast equipment failures, thus minimizing downtime and reducing maintenance costs (Kowalczyk & Buxmann, 2014).

Similarly, IoT-enabled tracking systems in retail allow for optimizing inventory and supply chains based on real-time demand patterns. Digital technologies also enhance customer interaction, enabling dynamic adjustments to service offerings that cater to evolving needs (Wasim et al., 2024). As businesses adopt these tools, they improve service delivery and gain competitive advantages by aligning operations with the complexities of contemporary marketplaces. The strategic deployment of such technologies underscores their transformative potential in service innovation, positioning them as essential components in the broader transition to digital service ecosystems (Gebauer et al., 2021).

The transformative potential of servitization in manufacturing industries has been significantly amplified through integrating digital technologies, marking an evolution from its original conceptualization. Initially, servitization referred to adding service components to traditional product offerings to create supplementary value. This framework was rooted in a product-centric approach, wherein services functioned as ancillary mechanisms to enhance the utility of tangible goods (Monroy-Osorio et al., 2023; Sjödin et al., 2020). However, with the advent of digital technologies, the concept has expanded to include digital servitization, where the core of value creation shifts from the product to the service ecosystem enabled by digital tools. This transformation is underpinned by Organizational Information Processing Theory (OIPT), which emphasizes the need for organizations to align their structures and processes with the increasing demands of information-rich environments (Haußmann et al., 2012). By integrating technologies such as IoT, AI, and advanced analytics, digital servitization enables firms to deliver comprehensive solutions beyond physical products, incorporating real-time monitoring, predictive capabilities, and tailored customer interactions (Corner et al., 1994). Therefore, resulting findings in the present research finds that manufacturing companies now leverage IoT-enabled devices to monitor machinery performance and anticipate maintenance needs, reducing costs and enhancing productivity (Monroy-Osorio, 2024a). By embedding digital technologies within their strategic frameworks, firms address customer expectations and adapt to the rapidly changing dynamics of global markets, ensuring their relevance and competitiveness in a digital-first world.

Building upon the foundations laid by servitization, digital service innovation (DSI) represents a paradigm shift in the strategic orientation of manufacturing firms. Unlike traditional servitization, which primarily focuses on augmenting products with additional services, DSI leverages digital technologies to innovate the design and delivery of services (Opazo-Basáez et al., 2022). This innovation allows companies to transition from reactive service provision to proactive and predictive engagement models. By integrating data analytics, AI, and IoT, firms can anticipate customer needs, optimize operations, and enhance the overall value delivered through their services. For instance, AI-driven platforms analyze customer behaviour and feedback, enabling firms to refine service offerings dynamically. Such platforms are increasingly used in predictive analytics, supply chain optimization, and personalized customer interactions (Kowalkowski et al., 2023).

Moreover, DSI plays a critical role in reshaping supply chain strategies, as firms employ real-time data to optimize logistics, reduce waste, and respond to market demands with agility. The study also reveals that DSI fosters organizational adaptability, allowing firms to navigate uncertainties and seize opportunities in volatile market conditions (Häikiö & Koivumäki, 2016). As digital technologies become integral to strategic planning, they redefine the parameters of business success, shifting the focus from traditional efficiency metrics to broader considerations of innovation, resilience, and value co-creation. This shift enhances operational efficiency and creates new avenues for growth, positioning firms to lead in the evolving digital economy. Consequently, DSI is a transformative tool that aligns technological capabilities with strategic objectives, enabling firms to sustain their competitive edge in a rapidly digitizing landscape (Vargo et al., 2023).

Despite its immense potential, integrating digital service innovation and advanced technologies poses significant challenges that must be addressed to realize their full benefits. One of the primary obstacles is the complexity of managing and interpreting the vast quantities of data generated by IoT devices, sensors, and AI systems (Coreynen et al., 2023). Data quality, security, and privacy are critical, as these factors directly impact the reliability of decision-making processes and customer trust. Additionally, the adoption of DSI often requires substantial investment in technological infrastructure, human capital, and organizational restructuring, which may strain financial and operational resources (Ranjan & Foropon, 2021). Furthermore, ethical concerns related to AI—such as algorithmic biases, lack of transparency, and potential misuse of data—highlight the need for robust governance frameworks to oversee the deployment of these technologies. The dynamic nature of digital ecosystems also necessitates continuous innovation and adaptability, demanding that organizations remain agile and responsive to emerging trends and challenges. Addressing these issues is essential for organizations to fully harness the transformative potential of DSI while mitigating its associated risks (Favoretto et al., 2022; Manser Payne et al., 2021). By implementing effective governance strategies and fostering a continuous learning and innovation culture, firms can overcome these challenges and position themselves for sustainable growth. This exploration of challenges also serves as a bridge to the next phase of this discourse, which examines the intersection of DSI and sustainability, exploring how digital technologies can be leveraged to achieve broader ecological and social objectives in the digital era (Cenamor et al., 2017).

1.3 Servitization Theory and the Efforts Toward a Future, Sustainable World

The evolution of servitization theory has moved far beyond its initial objective of transitioning from product-based portfolios to service-oriented models. This transformation has created an advanced, digital, and intelligent ecosystem that integrates essential, intermediate, and advanced services into a coherent framework. This evolution signals a shift in organizational priorities, emphasizing the need for ethical and sustainable practices that align economic objectives with broader societal and environmental imperatives (Kohtamäki et al., 2022; Verhoef et al., 2021). Historically, servitization focused on improving customer value and resource efficiency by bundling services with products. However, adopting digital tools such as artificial intelligence (AI), the Internet of Things (IoT), and advanced analytics has expanded its scope, enabled a deeper understanding of customer needs and created tailored solutions (Monroy-Osorio, 2024a). This transition reflects a broader organizational commitment to embedding ethical considerations into business strategies, particularly manufacturing. Through digital servitization, companies can foster resource-efficient practices, reduce waste, and promote sustainable consumption patterns. Manufacturers are better positioned to address the growing demand for sustainable and ethical business models by prioritizing value co-creation and fostering human-centered approaches (Kamp et al., 2023; Kohtamäki et al., 2020). This ongoing evolution of servitization reframes competitive strategies and supports a more balanced relationship between corporate objectives and societal responsibilities. As these advanced models gain traction, they enable firms to contribute to a sustainable future by designing services that are not only economically viable but also environmentally responsible and ethically sound (Vilkas et al., 2022).

The intersection of servitization and sustainability goals illustrates the role that digitally enabled strategies play in advancing environmental management and sustainable practices. This convergence highlights how service-oriented approaches can address global challenges such as climate change, resource scarcity, and waste reduction (Kohtamäki et al., 2024). Digital-first strategies leveraging IoT, AI, and blockchain technologies allow firms to precisely monitor, manage, and optimize their operations. For example, IoT-enabled sensors collect real-time energy use and emissions data, enabling manufacturers to identify inefficiencies and implement corrective actions. Similarly, AI-driven analytics facilitate predictive maintenance, ensuring machinery operates at peak efficiency while minimizing resource consumption and downtime. These tools also support the development of circular economy models, where materials are reused, recycled, or refurbished to extend their lifecycle and reduce waste (Falcke, Zobel, Yoo, et al., 2024).

Additionally, user-focused services are central to these efforts, prioritizing customer satisfaction while minimizing environmental impacts. Subscription-based models, pay-per-use frameworks, and shared ownership initiatives exemplify how businesses can provide value to customers without encouraging overproduction or underutilization of goods (Keiningham et al., 2007; Mccollough et al., 2000). By aligning customer-centric service strategies with sustainability objectives, companies can reduce their ecological footprint while enhancing transparency and accountability. Integrating digital tools and user-focused approaches thus represents a significant step in aligning corporate operations with global sustainability targets, fostering a culture of innovation and continuous improvement essential for addressing today's environmental challenges (Van der Byl & Slawinski, 2015).

The historical evolution of servitization, from craft production to mass production, segmentation, and advanced service models, provides valuable insights into integrating sustainability objectives within manufacturing strategies. As depicted in the provided framework, servitization in its current form emphasizes first-degree price discrimination coupled with technology upgrades to tailor offerings for individual customers (Monroy-Osorio et al., 2023). This approach enhances customer satisfaction and aligns with the broader agenda of promoting sustainable practices. In earlier stages, such as mass production, efficiency was prioritized over environmental considerations, often resulting in significant resource wastage. Segmentation introduced some degree of customization, yet it remained constrained by the limitations of traditional manufacturing processes (Hallowell, 1996). The modern servitization framework addresses these historical shortcomings by leveraging digital technologies to create adaptive, responsive, and sustainable service ecosystems. For example, the emphasis on treating each customer differently through advanced analytics allows firms to optimize resource allocation and reduce unnecessary production (Park et al., 2019).

Likewise, incorporating net-zero principles into servitization strategies highlights the potential for manufacturing firms to reduce their carbon footprint significantly. Technology-enabled practices such as energy-efficient production methods, renewable materials, and real-time emissions monitoring exemplify how firms can achieve environmental goals while maintaining economic viability (Stern & Valero, 2021). These advancements underscore the transformative potential of servitization as a mechanism for integrating ethical and sustainable considerations into business models. By connecting the historical trajectory of servitization with contemporary sustainability efforts, this approach demonstrates how manufacturing firms can balance the imperatives of customer satisfaction, economic efficiency, and environmental stewardship.

Nonetheless, despite its significant potential, integrating servitization with sustainability goals presents challenges that require careful navigation. One of the foremost obstacles is the financial and operational cost of transitioning to sustainable service ecosystems (Valtakoski, 2017). Implementing advanced technologies such as IoT, AI, and blockchain demands substantial investments in infrastructure, workforce training, and organizational restructuring. These costs can be prohibitive, particularly for small and medium-sized enterprises that need more resources than giant corporations. Additionally, the reliance on digital tools raises concerns about data security, privacy, and equitable access, especially in regions with limited technological infrastructure (Falcke, Zobel, Yoo, et al., 2024; Piscicelli, 2023). Ethical challenges also arise, including the potential for algorithmic biases and the misuse of customer data, which could undermine trust and transparency in service delivery (Paiola et al., 2021). Therefore, achieving this alignment with dynamic sustainability targets, such as net-zero emissions, necessitates continuous innovation and adaptability, placing additional strain on organizational resources. These challenges highlight the need for collaborative approaches involving policymakers, industry leaders, and academic institutions to establish clear standards and support sustainable servitization practices (Falcke, Zobel, Comello, et al., 2024).

Conclusively, Servitized firms are addressing these barriers, and it is critical to unlocking servitization's full potential as a sustainability driver. By integrating servitization and sustainability manufacturing firms faces a complex yet promising pathway for seeking to align their operations with global environmental and ethical objectives. By fostering a culture of innovation, collaboration, and accountability, organizations can overcome these challenges and position themselves as leaders in the transition toward a more sustainable and equitable industrial landscape (Edwards, 2021). This exploration of challenges is a foundation for further research and discussion, emphasizing the importance of strategic alignment in achieving long-term sustainability goals.

CHAPTER 2. RESEARCH SCOPE

2. Research question and objective of the thesis compendium

The first article highlights that the first research gap emerges from the transition from mass consumption to servitization. While the literature extensively explores how servitization shifts value creation from products to services, it remains primarily centred on traditional goods-based models (Kohtamäki et al., 2018; Rabetino et al., 2023). Although this transition is central in redefining business practices, The research identifies a lack of comprehensive frameworks integrating operations and pricing strategies with servitization principles. Specifically, a limited exploration exists of how technological advancements—such as IoT, AI, and digital sensors—can enhance servitization by transforming operational efficiencies and customer engagement (Monroy-Osorio, 2024a). Furthermore, the discussion often treats production and service strategies as discrete entities, overlooking opportunities to merge them into cohesive, technology-enabled frameworks. This gap is particularly evident in sustainability, where servitization's potential to support long-term environmental goals remains underexamined (Opazo-Basáez et al., 2024). Although servitization fosters resilience and adaptability in business models, its connection to digital innovation and sustainability practices requires further study (Monroy-Osorio, 2024b). The interplay between historical production models, technological integration, and sustainable servitization strategies remains fragmented, underscoring the need for holistic approaches that align servitization with modern technological and environmental imperatives.

Furthermore, the second research gap arises from the mediating role of digital service innovation (DSI) in enhancing business performance, as discussed in the second article. The article underscores DSI's transformative potential in leveraging AI and by-product data to refine decision-making and improve organizational efficiency. However, the literature often examines DSI and AI as separate entities, neglecting their combined impact on strategic business outcomes (Opazo-Basáez et al., 2022). While previous studies have demonstrated that DSI enhances operational efficiency and customer engagement, the mechanisms through which AI mediates these effects remain poorly understood. Using by-product data, such as contextual and customer feedback information, is underutilized despite its potential to inform service strategies and enhance digital ecosystems (Dubey et al., 2020; Sorescu, 2017). The research article identifies Organizational Information Processing Theory (OIPT) as a promising framework for aligning information flows with decision-making processes. Nevertheless, research seldom applies OIPT with AI to analyze how firms can optimize by-product data for business performance. This gap limits organizations' ability to fully exploit AI's capabilities in refining service innovation models. It underscores the need to examine how DSI and AI interact within digitally enhanced ecosystem (Haußmann et al., 2012; Mikalef & Gupta, 2021).

Finally, the third research gap concerns to integrating digital sustainability strategies into net-zero initiatives, as explored in the third article. While digital tools, such as IoT and AI, are recognized for their potential to support environmental management, the research highlights the limited practical application of these technologies in achieving sustainability objectives. Existing research emphasizes the theoretical benefits of digital-first and digitally enabled strategies, often overlooking their operational complexities and challenges. For instance, IoT and AI can enable predictive maintenance, optimize energy usage, and reduce waste, but organizational and technological barriers frequently constrain their adoption. Furthermore, there is a lack of focus on how these digital strategies can support the transition from traditional linear production models to circular and regenerative systems (Opazo-Basáez et al., 2018; Paiola et al., 2021). The research describes a disparity in how firms across industries implement digital sustainability practices, particularly in sectors with legacy systems or limited access to advanced technologies. This inconsistency indicates the need for more inclusive frameworks that address firms' diverse capabilities and constraints. Additionally, the ethical and data governance challenges associated with digital technologies, such as data privacy and security, remain underexplored in the context of sustainability strategies, leaving significant room for further investigation.

Collectively, these gaps highlight the need for comprehensive research to explore how digital technologies are reshaping servitization theory and practices, particularly in fostering sustainable strategies while enhancing business performance. Although each article addresses distinct dimensions of servitization, specifically through service innovation, the interactions between varying levels of servitization—basic, medium, and advanced—and their influence on business practices, performance, and sustainability remain insufficiently explored in the current literature (Huikkola et al., 2020; Rabetino et al., 2017). This compendium aims to fill these gaps by examining the convergence of servitization theories and strategies to tackle modern business and environmental challenges. A research gap emerges from the paradox of economic growth: while expanding economies and industries generate wealth and employment, they simultaneously exert unprecedented pressures on vital planetary systems. Despite this contradiction, economic growth remains a central strategic objective for businesses and economies worldwide. Therefore, the following investigation seeks to determine how serviced companies reconcile this paradox within their strategies, particularly in advanced services. The existing literature focus in different ecosystems, and it's in the needs on focus in connects servitization theories and strategies with business performance and sustainability objectives, especially regarding the mediating role of digital and non-digital technologies, like artificial intelligence (AI), in driving performance and achieving net-zero goals. Based on these considerations, the following research question arises:

How can integrating servitization strategies and service innovation drive sustainability initiatives while enhancing business performance?

To address this question, the present research examines servitization from a historical perspective, tracing its evolution to the present, where technology plays a fundamental role. The study focuses on firms incorporating essential, medium, and advanced services into their portfolios, analyzing how these service integrations and technological approaches improve business performance. Furthermore, this research evaluates how such services, alongside technological advancements, support the fulfilment of sustainability strategies and objectives by implementing the net-zero framework. By integrating and expanding the existing knowledge within the servitization research community, the presented research seeks to demonstrate how servitization strategies contribute to company growth while simultaneously addressing global sustainability challenges. Table 1 summarizes the temporal dimensions (past, present, and future) explored in this compendium.

Aspect	**Historical Foundations (Past)**	**Contemporary Innovations (Present)**	**Forthcoming Sustainability Efforts (future)**
Economic Evolution	Transition from agrarian economies to industrial mass production.	Service-oriented models leveraging digital tools such as AI, IoT, and advanced analytics to enhance service efficiency and customer engagement.	Fully integrated ecosystems that emphasize circular economies, resource efficiency, and alignment with global sustainability goals.

Servitization Framework	Originated as a response to goods-centered paradigms, introducing service marketing as an add-on to product strategies.	Digital servitization: Shift from product augmentation to service ecosystems driven by real-time data, predictive analytics, and advanced customer personalization.	Advanced ethical frameworks that embed sustainability into every stage of service design and delivery, focusing on human-centered and environmental considerations.
Service Innovation	Focused on enhancing product offerings through basic service additions, often limited to customer support or maintenance.	Leverages digital technologies to create data-driven, customer-centric service models, emphasizing personalization and adaptability.	Fully integrates service ecosystems into manufacturing and supply chains, prioritizing sustainability, ethical practices, and value co-creation.
Key Technologies	Mechanization during the Industrial Revolution set the stage for mass production.	Digital tools like IoT, AI, sensors, and blockchain enable proactive and adaptive service delivery, real-time monitoring, and predictive maintenance.	Intelligent, self-evolving systems leveraging AI and IoT to enable net-zero manufacturing, energy efficiency, and sustainable value chains.
Sustainability Strategies	Industrialization led to resource depletion, environmental degradation, and socio-economic inequality.	Adoption of circular economy principles and digital-first strategies to optimize resources, reduce waste, and minimize carbon footprints.	Integration of net-zero principles, renewable energy sources, and sustainable supply chain practices into the core of manufacturing and service ecosystems.
Customer Focus	Early mass production models focused on standardized goods with limited customization.	User-focused models enabled by digital technologies offer subscription-based services, pay-per-use frameworks, and tailored customer solutions.	Emphasis on treating customers as unique stakeholders through ethical price discrimination and service customization, promoting equitable and sustainable engagement.
Challenges	High environmental costs, lack of sustainability considerations, and externalization of impacts during industrialization.	Complexity of managing vast data ecosystems, ensuring data privacy and security, and addressing financial and operational strains in transitioning to digital servitization.	Ethical concerns such as algorithmic bias, equitable access to technology, and the financial viability of maintaining cutting-edge sustainable practices.
Theoretical Contributions	Introduction of service-dominant logic by Vargo and Lusch, challenging goods-focused marketing paradigms.	Organizational Information Processing Theory (OIPT) guides firms in adapting to information-rich environments enabled by digital tools and strategies.	Integration of servitization, digital innovation, and sustainability theories to create adaptive frameworks for ethical and environmentally conscious service ecosystems.

Industry Examples	Mass production in manufacturing and segmentation strategies with limited environmental foresight.	IoT sensors in manufacturing, predictive maintenance in healthcare, and subscription-based services in the automotive sector foster operational sustainability.	Expansion of adaptive pricing and service models to ensure fair access and equitable resource allocation, aligned with ethical and sustainable objectives.

Table 1: *Servitization seen as a progression from historical foundations to contemporary innovations and future sustainability efforts*

CHAPTER 3. METHODOLOGY

3. Methodology implemented in the compendium

3.1 Methods

The methods employed in the three papers collectively aim to explore the intersection of servitization, digital technologies and sustainability frameworks using diverse yet complementary approaches. The first paper adopts a conceptual and historical framework, analyzing the evolution of servitization through a qualitative lens. Key theoretical underpinnings and historical models—such as mass consumption and segmentation—are reviewed to highlight their connections and relevance to modern business practices. Operations and pricing strategies, referencing Porter's competitive framework, are integrated to propose a conceptual model that aligns servitization principles with cost-efficiency and differentiated market approaches. This methodology provides a theoretical lens for understanding how servitization strategies influence contemporary business ecosystems while raising pertinent questions about their integration with digital technologies.

On the other hand, the second paper utilizes a quantitative research design, employing general structural equation modelling (GSEM) to assess the relationship between DSI, artificial intelligence (AI), and business performance. Data is drawn from the Iberian Balance Analysis System (SABI) database and complemented with a targeted Qualtrics survey. The study focuses on Spanish manufacturing firms, spanning business-to-business (B2B) and business-to-consumer (B2C) contexts. The survey captures information on how AI mediates the impacts of DSI on key performance metrics, emphasizing the role of contextual and by-product data in enhancing decision-making processes. Organizational Information Processing Theory (OIPT) serves as the theoretical framework, guiding the analysis of information flows and their alignment with operational structures. This methodological approach enables the identification of actionable insights into the synergistic relationship between DSI and AI within digitally enhanced ecosystems.

Finally, the third paper adopts a mixed-methods approach, combining quantitative data collection with qualitative insights to explore digital-first and digitally enabled strategies for achieving net-zero objectives. The study examines 354 medium-sized Spanish manufacturing firms employing IoT and AI technologies to analyze their contributions to environmental management and sustainability goals. Firms are categorized based on their adoption of digitally enabled versus digital-first strategies, offering a framework for understanding how digital tools optimize resource use, reduce emissions, and foster sustainable practices, called the Net-Zero approach.

3.2 Sample

The combined sample across the three studies includes 354 medium-sized manufacturing firms located primarily in Spain, representing industries with varying degrees of digital adoption and sustainability integration. The first paper adopts a theoretical perspective and does not utilize a specific sample; instead, it relies on secondary sources to examine historical trends and theoretical frameworks. The second paper's sample is drawn from the SABI database, which provides comprehensive financial and operational data on Spanish firms. This dataset is complemented by responses to a targeted survey distributed via Qualtrics, designed to capture insights into firms' digital transformation efforts and the role of AI in strategic decision-making. The third paper expands the analysis by categorizing firms based on their digital sustainability strategies, distinguishing between digitally enabled practices—such as IoT for process optimization—and digital-first approaches, which integrate AI into the foundational design of sustainability initiatives. This stratification allows for a detailed examination of the sample's diversity and relevance to broader digital transformation and sustainability discussions.

3.3 Variables

The studies incorporate diverse variables to address their respective research objectives. In the first paper, the primary variables are conceptual, focusing on historical production models (e.g., craft, mass production, segmentation, servitization) and their strategic alignment with operations and pricing strategies. These variables are examined qualitatively to understand their evolution and implications for modern business practices. The second paper operationalizes its variables quantitatively, with digital service innovation (DSI) serving as the independent variable, business performance (BPer) as the dependent variable, and artificial intelligence (AI) as a mediating variable. Additional contextual variables include customer usage data and customer feedback data, categorized as by-product data, which influence the mediating role of AI. The third paper emphasizes sustainability-related variables, differentiating between digitally enabled and digital-first strategies. Key variables include IoT usage for resource optimization, AI deployment for emissions management, and the integration of net-zero frameworks. These variables are validated in previous literature in servitization, business performance, strategy, among others. It was analyzed to assess their impact on environmental sustainability, operational efficiency, and long-term business viability. These variable sets provide a comprehensive basis for examining the interplay between servitization, digital innovation, and sustainability in contemporary business contexts.

CHAPTER 4. COMPENDIUM ARTICLE 1

Chapter 4. Compendium Article 1

Consumer goods: from mass consumption to servitization

Reference: Monroy-Osorio, J. C., Opazo-Basáez, M., & Vendrell-Herrero, F. (2023). Consumer goods: from mass consumption to servitization. In *Handbook of Industrial Development* (pp. 232-247). Edward Elgar Publishing.

https://doi.org/10.4337/9781800379091.00024

Abstract:

This chapter draws on price discrimination and historical production models to build price and operations strategy typologies in manufacturing. Historically, manufacturing firms have been unable to find production models that achieve optimal price and operations strategies. For instance, craft production could possibly achieve optimal price discrimination (first-degree discrimination) but lower operational performance. In contrast, mass production dramatically improved operational performance simply by offering volume discounts to attract demand (second-degree discrimination) or segmentation (mass customization), which could only achieve third-degree price discrimination. However, this research presents a relatively new production model that can offer price and operational optimality jointly, i.e., the servitization of manufacturing. In servitization, manufacturing firms add services to foster closer and richer relationships with customers (front-end), and digital technologies to improve logistics and inventory management (back-end). Here it is argued that, by doing so, servitization enables first-degree price discrimination to be established via product customization, and production efficiency via built-in digital production facility and product capabilities.

14. Consumer goods: from mass consumption to servitization

Juan Carlos Monroy-Osorio, Marco Opazo-Basáez and Ferran Vendrell-Herrero

1 INTRODUCTION

The transition from consuming goods to consuming services is a subject of great interest to academics and has been examined from various perspectives. The vast majority of management research traditionally adopts a manufacturing, and therefore goods-based, perspective (Lee, Yoo and Kim, 2016). However, economies around the world have long reached the age of service-driven economic growth. Services are now indisputably significant to economies, determine corporate and personal well-being, and are increasingly edging toward traditional goods consumption domains (Martin, Schroeder and Bigdeli, 2019). As a result, consumption is increasingly shifting from mere goods-related transactions toward service-related transactions (Spring and Araujo, 2013). This development has recently been boosted by technological advancements and innovative production models, enabling consumers to use material products via services without the need for ownership (Frank et al., 2019). The growing industrial concern about sustainability and the development of better practices of manufacturers has encouraged servitization to compete by integrating technology and services into the firm's productivity, contributing to the necessary development of the industry ecosystem (Opazo-Basáez, Vendrell-Herrero and Bustinza, 2018).

Understanding how production has evolved to contribute to this transition is imperative. Its impact on modern history has been enormous, since it has given rise to the spread of goods and products across societies, countries and regions (Grundy, 2006). These models can be encapsulated by craft production, mass production, segmentation and servitization. Understanding their connections, strengths and weaknesses in historical and present-day contexts allows each model's significance to be interpreted in business scenarios (Argyres et al., 2020; Gomes et al., 2021). However, the integration of operations and price strategies, a model first introduced by Porter (1997), is not widely explored, and normally seen as separate. There are calls for the convergence of different strategic viewpoints or levels (Bailey, Pitelis and Tomlinson, 2020). So, can industry combine these strategies with the transition from products to services in new production models?

The chapter presents a review of operations and price strategies and their impact on business growth. The objective is to put forward a proposal for a framework that allows Porter's price strategies and production models to be integrated via operations strategies by using the servitization product model, which successfully combines operations (cost-efficiency) and pricing. This analysis will lead to conceptual discussions on how the evolution of different production models relates to demand, the market and therefore the consumer, and will raise questions that help to better understand the significance and relevance of such models at strategic historical points in the industrial development of firms. The research will also raise questions that will allow industry to expand its horizons, entailing important implications for practitioners and policymakers.

2 THEORETICAL BACKGROUND

2.1 Porter's Competitive Strategies

Competition has driven industry to advance and innovate in different scenarios, and is caused, according to Porter, by two competencies: operations and price strategies (Porter, 2008; see also Grundy, 2006), which can build an ecosystem still under discussion in the academic community. Porter simplifies the description of strategic orientations by limiting it to cost leadership, differentiation and market segmentation (or focus). Market segmentation is narrow in scope, while both cost leadership and differentiation are relatively broad in market scope, and increase the profit impact of strategies (Lavoie and Liu, 2007). Empirical research on profit impact indicates that firms with high market share are often profitable, but many firms with low market share have the same advantage (Hefley and Murphy, 2008). The least profitable firms are those with moderate market share.

This is sometimes referred to as the 'hole-in-the-middle' problem. Porter explains that firms with high market share are successful. Nevertheless, they must pursue a pricing strategy. According to Porter, firms in the middle are less profitable because they do not have a viable generic strategy – that is, to combine the firm's product and cost (supply) with the characteristics of target market segments (demand) (Porter, 2008). However, different pricing strategy combinations, such as market segmentation with product differentiation, cannot be performed due to the potential conflict between cost minimization and the additional cost of value-added differentiation (Björkdahl and Holmén, 2013). According to Porter, an operations strategy is crucial to differentiation by placing emphasis on the efficient production of high volumes of standardized products so that the firm can possibly take advantage of economies of scale, and experience curve effects (Porter, 1997). The product is often essentially a no-frills product produced at relatively low cost and made available to an extensive, broad customer base (Grundy, 2006).

2.2 Price Strategies as a Way of Competing

Understanding and defining the main price strategies as a whole is an approach that academics have developed in recent research (Stole, 2007). Moreover, the studies show that most academics agree on defining price discrimination as one of the most common, effective and traditional actions that companies take when implementing market strategies for business growth (Grundey and Griesiene, 2011). Discrimination strategies have been developed in different dimensions of study, including the financial dimension, whose main component is profit maximization; economic dimension, focusing on the market and its properties; and marketing dimension, where price discrimination definitions reside in the ability that companies acquire to compete by means of price strategies in different markets with high or low segmentation (Ekelund, 1970). Table 14.1 shows the definitions accepted by the literature according to the above dimensions.

Table 14.1 *Description of price discrimination strategies (a selection of dimensions)*

Source	Description of Price Discrimination Strategies	Dimension
Phlips (1983, p. 5)	Price discrimination occurs when the same commodity is sold at different prices to different consumers	Economic
Bishop and Colwell (1989)	One kind of behavior that is consistent with profit maximization is called price discrimination. Price discrimination is the practice of charging different buyers different prices according to how responsive consumers of the particular good or service are to a change in its price	Financial
OECD (2003)	Price discrimination occurs when customers in different market segments are charged different prices for the same good or service for reasons unrelated to costs. Price discrimination is effective only if customers cannot profitably re-sell the goods or services to other customers	Financial
Dibb and Simkin (2004, p. 159)	Price discrimination: a policy whereby different prices are charged in order to give a particular group of buyers a competitive edge. It is important that a marketer ascertains that such discrimination does not break any laws	Marketing
Drake (2005, p. 4)	Price discrimination is the practice of charging different consumers different (marginal) prices for the same economic good. These price differences cannot be explained by the difference in marginal cost of making the goods available for the various consumers	Economic
Lancaster and Withey (2007, p. 153)	Segmented/differential pricing (price discrimination) – companies will often adjust their basic prices to allow for differences in customers, products, location, time/season and so on. Essentially, the company sells its products via two or more processes, even though price difference is not always based on cost differences. Often known as price discrimination, this approach to price adjustments can be very effective at maximizing demand and company revenue	Marketing
Armstrong (2006, p. 1)	In broad terms, it can be said that price discrimination exists when two 'similar' products that have the same marginal cost of production are sold by a firm at different prices	Financial
Farrell and Hartline (2008, p. 247)	Price discrimination occurs when firms charge different customers different prices. Price discrimination is very common in business markets, where it typically occurs between different intermediaries in a supply chain. In general, price discrimination is illegal unless the price differential is based on the actual cost differences of selling products to one customer in relation to another	Marketing
Mankiw, Quah and Wilson (2009, p. 326)	It has been assumed that monopolies charge all customers the same price. Yet, in many cases, firms sell the same good to different customers at different prices, even though the production costs for all customers are the same. This practice is called price discrimination	Economic

Source: Grundey and Griesiene (2011).

Although these dimensions help to clarify the definition objectives set by different academics, their strategic implementation has led to a historical breakdown that is allowing them to be shared and applied, cutting across different levels. The first level is first-degree price discrimination, whose aim is to differentiate price according to perceived value in a limited market, such as highly personalized luxury products with limited demand. Second-degree price discrimination strategies can lead to exponential business growth in global markets, with standardized products primarily aimed at mass purchase volume. They employ strategies such as discounts, enabling quicker inventory turnover. However, this sacrifices personalization for the sake of a wider market. Furthermore, these dimensions' third cross-cutting level is third-degree price discrimination, whose aim is business growth in markets with widespread

Table 14.2 Defining degrees of price discrimination according to dimension

Degree of Price Discrimination	Financial Definition	Marketing Definition	Economic Definition
First-degree price discrimination	A different price for each customer depending on demand intensity	Separating the entire market into each individual consumer and charges the price they are willing and able to pay	Identical goods are sold at different prices to each individual consumer
Second-degree price discrimination	The seller charges bulk buyers less	Selling off product packages considered better value for money than previously published/advertised prices	Charging lower prices for larger quantities. This degree also includes early-bird discounts
Third-degree price discrimination	The seller charges different types of buyers different amounts	Charging different prices for the same product in different market segments. The market is usually divided in two ways: according to time or geography	Results in the most sales in each segmented consumer 'group'

Source: Grundey and Griesiene (2011).

segmentation. Table 14.2 summarizes first-, second- and third-degree price discrimination strategies in their academic dimensions.

2.3 Operations Strategies

Primarily studied by academics and industry itself, numerous production paradigms have emerged throughout history that have proven to be key in society's economic and industrial progress. However, four models have emerged to lead product innovation and deliver to a market in need – namely, craft production, mass production, segmentation and servitization. Their operations strategies can be broken down into three ecosystems: manufacturing, services and product-service systems (PSSs). The first model was craft production, the standard approach to manufacturing in the pre-industrialized world, centered around high quality, personalization and exclusiveness based on skilled manual labor (Solomon and Mathias, 2020). It does, however, entail a collateral effect. While the product may be of extremely high quality, exclusivity can be detrimental to a wider market.

A second model, called mass production, was therefore developed to create standard goods for a mass market, transforming businesses throughout the 20th century by concentrating their efforts on the undisputed aspiration of industry – namely, industrial efficiency (Hara, Sato and Arai, 2016; Hu, 2013). The fact that technological development focused on heavy machinery and increasing the capacity of large firms to switch production rapidly from product to product (Meier, Roy and Seliger, 2010; Zabihi, Habib and Mirsaeedie, 2013) was one of the most discordant aspects of the mass production model. Hence, in the late 1970s, segmentation emerged as a solution to mass production. The third model, mass customization, centers on growing consumer demands, whilst benefiting from global production by using the latest technology. It was brought about by several essential concepts and technologies, which include product-family architecture, reconfigurable manufacturing systems and delayed differentiation (Tomlinson, 2010).

While the goals of mass production and mass customization can be described as economies of scale and economies of scope, the consumer's role changes from that of 'buyer' to 'chooser,' which calls for different approaches capable of yielding more responsive

Table 14.3 Operations strategies, benefits and challenges

Operations Strategies in Craft Production	Operations Strategies in Mass Production Models	Operations Strategies in Segmentation	Operations Strategies in Servitization
Benefits			
Alignment of strategy and target market Clear definition of competitive priorities Focus on quality Service adaptation to market segments Hard-to-measure performance	Alignment of strategy and target market Clear definition of competitive priorities Focus on sets of competitive priorities Technology Environmental and social issues	Alignment of strategy and target market Focus on sets of competitive priorities Technology Good alignment with suppliers	Merging of operations strategies in manufacturing and services Intense focus on customer and human resources Good alignment with suppliers Cost efficiency
Challenges			
Appropriate technological choices			
Good alignment of competitive priorities, business strategies and operations strategies			
Strategic alignment with the target market			
Good alignment with suppliers			
Balancing the roles of manufacturing and services			
Financial risk			

manufacturing systems (Stole, 2007). It is in this scenario that the four production models emerge. Servitization is determined by how the increased offering of more comprehensive market packages or 'bundles' of customer-focused combinations of goods, services, support, self-service and knowledge can add value to core product offerings (Vandermerwe and Rada, 1988). The literature has identified three general reasons for servitization: economic reasons, user needs and competitive reasons (Rabetino et al., 2021). Economic reasons include the pursuit of higher profit margins and income stability due to the services' resilience to economic cycles (Opazo-Basáez, Vendrell-Herrero and Bustinza, 2019). Changes in user needs relates to the fact that consumers increasingly demand a variety of different services. In the business-to-business (B2B) context, this involves focusing on core competencies, and is an additional reason for external services (Vendrell-Herrero and Wilson, 2017).

Servitization makes it economically advantageous for firms to extend the product's useful life, enabling constant revenue to be gained throughout the product life cycle, not simply from the specific transactions (Vendrell-Herrero, Gomes et al., 2021). The differences between manufacturing and service firms arise in relation to perishable, complex and multifunctional service activities. Becoming an industrial service provider is not, therefore, simply a question of offering adjustments, but rather an entire organizational change in focus of attention and managerial approach (Brax, 2005; Rajala et al., 2019). Vandermerwe and Rada (1988) describe the progression of how companies understand the servitization in industrial development by first considering the differentiation in goods or services, and then moving to offer goods combined with closely related services, and finally to a position where firms focus on the combinations of goods, services, support, self-service and knowledge. Servitization offering calls for a new way of thinking in relation to business strategy, business model and manufacturing model. Moreover, the company needs to broaden its definition of the value chain, shifting its focus from operational excellence to alliances with consumers (Kowalkowski et al., 2015). Table 14.3 shows the main operations strategies according to production model.

3 INTEGRATIVE FRAMEWORK

3.1 Operations and Price Strategies

Understanding how these dimensions are implicit in production model strategies is essential to understanding the rise of servitization in the industrial development (Vandermerwe and Rada, 1988). Craft production possessed limited customer reach, as sales were mainly restricted to customers who discovered craft products at small local shops, and through a few other channels. Growth thus involved activities such as building more storefronts (Solomon and Mathias, 2020). However, two critical convening factors altered this landscape. First, technology dramatically changed the growth opportunities available to artisan entrepreneurs. The rise of online marketplaces and social media marketing provided artisan entrepreneurs with new channels to display their products to a wider market (ibid.). Second, social movements fostered increased demand for handmade goods. The 21st century has ushered in a shift in consumer values, paving the way for the rise of an artisanal movement (i.e., makers). Hence, it is common to find first-degree price discrimination strategies based on personalization and high segmentation in craft production.

Companies expect exponential growth in this scenario, where mass production has historically had its greatest strengths, competing in small production and customization strategies in markets with homogeneous characteristics (Hu, 2013). Recent research shows that the mass production model has provided abundant access to mass consumer goods without discriminating markets, needs, geographies or publics. Nevertheless, it has triggered heavy consumption and given rise to concepts such as fast fashion, planned obsolescence and other strategies to the detriment of product quality, while, at the same time, it has increased production (Duguay, Landry and Pasin, 1997; Raddats et al., 2016; Sabel and Zeitlin, 1985).

Be that as it may, today's world, and industrial firms' development, are difficult to understand without the benefits of mass production related to its strategies for volume and availability and resulting accessibility to different markets. Many academic communities have spoken of concepts such as the democratization of consumption (Küçük, 2020), mass consumer goods, and the rise of the global market (Bianchi and Labory, 2006; Coveri et al., 2020; Matyushok et al., 2021), recognizing that there would be no simplification of the supply chain and availability in different markets without mass production. However, it would always need strategies based on broader price ranges than those offered by craft-type models and would no longer rely on the product and its components for value. Thus, second-degree price discrimination emerged as a strategic complement to this mode of production (Cortiñas, Chocarro and Elorz, 2019), whose main difference from the first degree was that it introduced volume, discount and promotion strategies. Hence, the connection between price, product and market entered into a previously unseen definition – namely, the price war – where the value is not perceived in relation to the product but rather to the end price associated with the market (Wang et al., 2020). In this scenario, mass production reaches a zenith in terms of availability, production and simplification.

By the time most companies fulfill their main objective of delivering mass consumer products to the global mass market, and the strategies associated with second-degree price discrimination contemplate new products within a standardized view of consumption, mass scale stagnation will not allow the firm to grow any further (ibid.). Mass customization as a production model begins with clear product, price, and market differentiation. It is thus transmuted into what has subsequently been called mass customization, which develops product personalization within mass production (Hu, 2013). Traditionally, segmentation or customization production models use strategies that cover more markets with fewer products whilst maintaining its characteristics adapted to consumption, among other variables. Third-degree price discrimination then becomes the basis of many segmentation strategies. An example of the use of this price strategy in segmentation can be observed in technology firms, where companies such as Apple, Microsoft and Dell satisfy the needs of different markets and segments via a portfolio of limited, differentiated products that, to a lesser or greater extent, adapt to geographies and consumption trends accordingly. As mass production grows and more products are included in the portfolio, mass customization must not take over. There must also be noticeable market and consumer differentiation enabling price discrimination based on outstanding value (Wang et al., 2017).

Recent investigations into the degree of price discrimination have revealed remarkable variations, due mainly to the entry of technologies enabling connections between individual or segmented markets at global level, such as social media, digital shopping channels, and digital banking (Cortiñas et al., 2019; Jenkinson, 2009; Stole, 2007; Vendrell-Herrero et al., 2018). In addition, traditional production models are increasingly exposed to these technologies, giving rise to mixed models that challenge theoretical concepts and encourage the development of new strategies yet to be defined and appropriated. Examples can be seen in Table 14.3, highlighting the most widely used price discrimination strategies in the past few decades.

Nonetheless, the inclusion of new media and technologies evidenced the need for a new production model offering a broader spectrum of product and market competition (Gomes et al., 2021; Qi et al., 2020; Wang et al., 2017). The paradigm of service as a product or as part of its portfolio has been worked separately in industrial development history. However, and for the advance of new business and production strategies, it requires a model whose center is not simply the beneficial relationship between the tangible and the consumer.

3.2 The Value of Servitization: The Benefit of Connected Working

Over the past two decades, academic and industry interest in services accompanying different manufacturing industries is growing and gathering constant momentum in the development and growth of different theories and fields (Qi et al., 2020; Sousa and da Silveira, 2019). As a theoretical concept, servitization has enabled industry and business portfolios to be increased, providing knowledge in business models and research that industry has yet to explore (Rabetino, Kohtamäki and Gebauer, 2017; Raddats et al., 2019; Vandermerwe and Rada, 1988). Some servitization experiences at global and local level have highlighted its potential, disentangling the elements shaping a product. These range from the different models involved in the product and its potential value to expertise gained by the roles and individuals developing the process into an industry focused on the pooling of experience, seen, for example, in knowledge-based business theory (Pistoni and Songini, 2017; Raddats et al., 2016). Servitization has created bridges between product, production and different roles, knowledge and experiences (Bustinza et al., 2018; Valtakoski, 2017).

To appreciate and comprehend how the servitization production model has evolved, it is essential to understand the role of service-dominant orientation (Valtakoski, 2017; Visnjic Kastalli and Van Looy, 2013). Nevertheless, whilst focusing on services, instead of integrating products and services, service-dominant orientation tends to ignore aspects relating to product development, competence and pricing. Servitization overcomes this problem of integrating products and services via product servitization or service productization according to the situation (Bustinza et al., 2018; Opazo-Basáez, Cantín and Campos, 2020).

For several academic researchers, understanding this competitive scenario proves key to understanding the rise of servitization as a production model (Luoto, Brax and Kohtamäki, 2017; Rabetino et al., 2021). Servitization adds value from the moment the service or product design is conceptualized and consequently adapted by consumers and their context (Opazo-Basáez, Vendrell-Herrero and Bustinza, 2022). Degrees of price differentiation and price discrimination possess a dynamism in servitization that has been little used in other production models and, in some cases, is unthinkable (Vendrell-Herrero and Wilson, 2017). Thanks to its flexibility, enabling the integration of services with products and value, competition between firms has been transformed, to the extent, for example, that alliances are being formed in specific processes requiring knowledge in order to gain pole position in differentiation strategies. An example of this is how Spotify, a music streaming service, connects with other firms such as Facebook, Google and Amazon to identify variables exogenous to its platform in order to build omnichannel profiles aimed at multimedia, virtual and face-to-face consumption of content. This would have previously been unthinkable in the music industry, whose segmentation was more limited to audio products (Jovanovic, Sjödin and Parida, 2021; Tian et al., 2022).

Servitization can therefore be a mechanism enabling firms to simultaneously deploy first-degree price and operations strategies based on the personalization and high segmentation of services and market-oriented products. Servitization prioritizes the consumer, adjusting production to more perceptive degrees of personalization than those used in the mass segmentation model. In this scenario, when first-degree price discrimination better exploits the benefits of flexible and personalized price strategies, servitization can be a bridge connecting dynamic technology and strategy upgrades with lower costs. Figure 14.1 presents the proposed

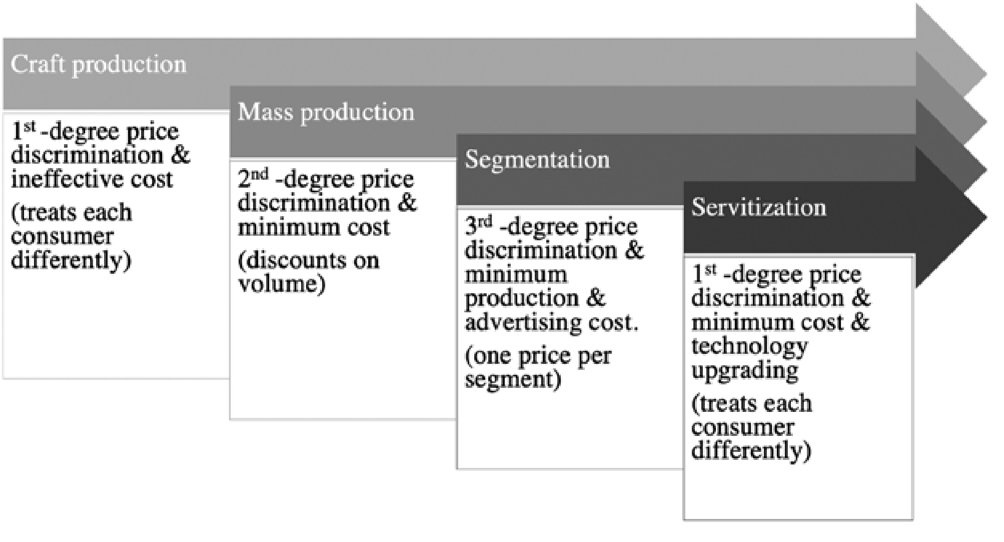

Figure 14.1 Framework for integrating operations and price strategies

framework, showing an evolution of the strategies in industrial development and how operations strategy can be connected with price strategies.

4 PROPOSITIONS

The aim of this section is to further elaborate on our model by comparing historical production models and analyzing their dominance according to their degree of knowledge and integration in relation to demand. Initially, mass production and mass customization are compared, followed by mass customization and servitization.

Since its inception, mass production has been the model used by business and industry for constant growth (Wang et al., 2017), a model that responded to the wider market needs of globalized demand. It has evolved with technological advances focusing on an infrastructure that is capable of maximizing profits whilst simplifying the value chain, and those forming part of it, throughout its performance (Qi et al., 2020; Sabel and Zeitlin, 1985). However, this model leads to sacrifices in quality and the perception of a homogeneous market, where competition between actors is reconciled in order to find differential value in second-degree price discrimination, which is based on volume and availability. Such competition in challenging scenarios leads to price wars whose differentiating value lies in discounts and its relationship with volume (Wang et al., 2020).

Historically, mass production has given rise to a revolution in how different products and materials associated with a portfolio are produced and distributed, and is always directed towards a single objective: responding to market demand (Sabel and Zeitlin, 1985). However, when advances in technology and the growing information and intelligence capabilities of firms are analyzed, substantial differences between mass production and the benefits of segmentation and personalization become evident in wider markets thanks to diversity and a differentiated product portfolio (Jenkinson, 2009; Stole, 2007). Additionally, production in the segmentation model produces smaller business portfolios since it is more efficient due to frequent trading with fewer demands.

An example can be seen in technology firms such as Apple, whose 1997 portfolio consisted of approximately 350 products, which later adopted a production model based on demand segmentation according to geo-referencing demographic and behavioral variables. This enabled regular consumers to be separated from expert consumers in more detailed market niches, resulting in just ten products in its portfolio in the same year. This led to a significant increase in revenue thanks to a better understanding of demand and an approach that brings about supply simplification by means of segmentation-based production models. In addition, the chance to innovate and develop products for new markets increases due to the fact that strategic efforts have focused on product innovation on a wider scale, unlike mass production. In relation to this behavior, the following proposition is put forward:

P1: In a system where mass production and segmentation coexist, segmentation will, on average, outperform mass production if the firm understands demand.

The mass customization production model enables specific market needs to be understood beyond the information provided by demand. This allows strategies associated with third-degree price discrimination to benefit from segmentation, such as pricing according to recurrence, geographic location, demography, as well as other strategies (Fogliatto, Da

Silveira and Borenstein, 2012). Its strength lies in its high degree of differentiation between consumers in the same market. Today, there are various definitions of customization depending on marketing angle focus, cost efficiency and design solutions.

One of the mass customization model's many characteristics is that it is a marketing and manufacturing technique combining the flexibility and personalization of custom-made products with low unit costs associated with mass production (Jenkinson, 2009; Qi et al., 2020; Stole, 2007). Segmentation and customization-based products and strategies can be broken down into three categories: (1) mass personification where products are mass produced but can be modified by the business to meet the consumer preferences identified via existing data on an individual; (2) mass customization or products that are mass produced where consumers are offered limited customization options; and (3) customer requests are tailored from beginning to end in the creation of a unique product.

Recent studies show a relationship between the segmentation and servitization production models, fueled by strategies such as customization and personalization (Benedettini, Neely and Swink, 2015; Cortiñas et al., 2019; Donio, Massari and Passiante, 2006; Stole, 2007). However, the results show that product innovation capability directly improves servitization. Although the direct effect of mass customization capability on servitization is not significant, it improves servitization indirectly by means of product innovation capability (Sousa and da Silveira, 2019). Segmentation models still focus on the product only according to personalization offerings and highly segmented market demands, thereby developing a specialized competitive offering.

Although third-degree price discrimination strategies lead to effective segmentation, industry's intense focus on making the product's business models profitable creates barriers and limits such strategies. Hence, servitization of the production model is required, where the focus is on the product–service relationship (Rabetino et al., 2021; Vandermerwe and Rada, 1988). Manufacturers face intense competition in global markets due to product commoditization, and modern manufacturing extends beyond tangible goods production (Opazo-Basáez et al., 2020; Sousa and da Silveira, 2019).

Service-oriented business models are currently seen as essential to industrial success. Therefore, integrating intangible services and tangible products has become a popular strategy for manufacturers to differentiate and gain a competitive edge. The fact that the servitization model benefits from digital technologies is an essential factor that can lead to improvement in operational efficiency due to customization associated with the product–service relationship (Vendrell-Herrero, Bustinza and Opazo-Basáez, 2021). Business models, known as platforms, offer different personalized or highly segmented products or services in order to engage consumers. Cases such as Uber and BlaBlaCar provide an example of operational effectiveness segmented by consumer needs, which may be the same consumer that has different needs associated with an equivalent service (Ranjbari, Morales-Alonso and Carrasco-Gallego, 2018).

Therefore, one of the main advantages identified in servitization is its ability to integrate not only product and service innovation, but also business growth strategies. Servitization combines operations strategies with price strategies, paving the way for growth in line with market and consumer demands. Previous research separated these strategic theories; however, the context in which servitization has been implemented has shown that both strategic models can be developed simultaneously. This context gives rise to the second proposition:

P2: In a system where segmentation and servitization coexist, servitization will, on average, outperform segmentation if the firm jointly deploys operations and price strategies.

5 DISCUSSIONS AND CONCLUSIONS

5.1 Academic Implications

This chapter puts forward a proposal to merge strategy and production management in the streams of literature by using a historical approach. To this end, the framework proposed combines dominant production models (e.g., craft, mass, segmentation and servitization) with price discrimination strategies (e.g., from first-degree to third-degree price discrimination). Moreover, servitization has in itself become a theory, a concept within the historical context of consumer goods, and now services, production (Rabetino et al., 2021). This research reveals that servitization is proving to be a return to craft/customized production, enabling first-degree price discrimination with cost-efficient production models. Mass production and segmentation use different forms of price discrimination to interact with demand, and achieve considerable cost reduction but lose consumer-based viewpoints in their decision-making (Stole, 2007).

The path has now been cleared for its theoretical development and has aroused the academic community's interest in production and its different models. It has allowed new theoretical grounds to be posited that broaden its horizons. The discussion surrounding servitization and other production models has given rise to constant debates on service monetization strategies, increasingly dynamic segmentation and hybrid business models, and has led to a re-examination of what is considered traditional mass consumption. Although many of these models persist due to the development of strategies in digital, technological and global ecosystems, it is essential to recognize that the inclusion of services has brought about an increase and merging of flows that were previously seen in parallel rather than intertwined. The vision of mass consumption and how it is to be transformed into consumer demand for services has driven the ecosystem, industry and companies to seek new strategies that stand out in an increasingly segmented and global market.

5.2 Managerial Implications

Although production models and price discrimination strategies have been widely studied, the acceptance of new models has proven difficult over the years. The framework lends itself to both theories being merged. Moreover, the observation of servitization and its implication in industry as a model to produce products and services can be approached from different strategic fronts, not simply from the supply viewpoint. Servitization and how it benefits industry in a globalized and dynamic market enables new competitive strategies that add explicit value and encourage business growth in traditional markets in ways not previously approached from a holistic, consumer market point of view (Raddats et al., 2019).

Furthermore, the research community's vision could be broadened to include other dimensions, providing insights into current phenomena and historical events, such as the impact of new technologies, increasingly digitalized markets and supply chains that are mindful of sustainability and accessibility challenges facing local and global consumption.

5.3 Industrial Policy Implications

Servitization has opened up a relationship between increasingly personalized, flexible and dynamic services and products combining high innovation, technology and digitalization. However, recent research has revealed certain sluggishness in the advancement of policies that contribute to business growth in highly industrialized regions (Labory and Bianchi, 2021). This chapter provides insight into the evolution of both the production models and growth strategies facing the market and demand. Industrial policy can benefit since servitization, by strengthening highly industrialized regions, facilitates the study of industry-oriented public policy and its relationship with the consumer in a dynamic context permeated by technology and digitalization (Vendrell-Herrero and Wilson, 2017). Industrial policymakers should stimulate regional servitization capacities to develop and transform industrial areas into highly competitive industries in dynamic markets (Bianchi and Labory, 2006).

By addressing this implication, the framework herein can benefit the current discussion on industrial policy by acknowledging the challenges and risks identified as external elements that make manufacturing growth difficult (Buckley et al., 2020). This study also contributes to the discussion on market regulation of industrial policy that provides protection when implementing servitized business models seeking practical orientation towards the market (Lafuente, Vaillant and Vendrell-Herrero, 2019). Such regulation, which includes operations and price strategies, business models, competition, and market, will broaden current discussion in the academic community.

Servitization is at the center of policymakers (Hojnik, 2016), and the creation of new regulations can benefit the industrial development of firms that had already chosen the servitization production model. Nevertheless, industries must be accompanied by a vision that recognizes its historical value, reviewing lessons learned and documenting the industrial history through the servitization lenses (Brax, 2005). While some sectors may fear and attempt to disregard servitization, it is unlikely that such attempts will yield substantial results (Bailey, Glasmeier and Tomlinson, 2019; Labory and Bianchi, 2021). It seems more constructive to embrace it as a developer working to the benefit of industrial development and economics in society.

5.4 Avenues for Further Research

Although the study presents a summarized and accepted vision of widely investigated concepts, a detailed study of current dynamic phenomena in medium-sized and small production enterprises is required. Additionally, it is essential to note that service monetization is still a subject of debate by academics and business. Phenomena such as de-servitization or the study of the impact of price-oriented strategies on business value chains are overwhelmed by the use of data unassociated with business growth. Data should relate to market evolution, as seen from the viewpoint of disciplines that have a substantial impact on the design and development of new strategies, and solid connections with product and service consumption. The framework proposed is a starting point to understanding the consumer impact and analyze the significance of production models and strategies in industrial development. A review of price discrimination strategies using market behavior variables would provide a predictive approach to demand, enabling businesses to concentrate their efforts on innovation.

It is hoped that this study facilitates linkages between seemingly distinct perspectives and sources of knowledge. Future researchers are urged to join forces across disciplines to shed light on the nature of the transitional processes that guide goods consumption increasingly toward service consumption.

REFERENCES

Argyres, N.S., De Massis, A. and Foss, N.J. et al. (2020). History-informed strategy research: the promise of history and historical research methods in advancing strategy scholarship. *Strategic Management Journal*, *41*(3), 343–68.

Armstrong, M. (2006). Recent developments in the economics of price discrimination. In R. Blundell, W. Newey and T. Persson (eds), *Advances in Economics and Econometrics: Theory and Applications, Ninth World Congress* (Econometric Society Monographs, pp. 97–141). Cambridge, UK: Cambridge University Press.

Bailey, D., Glasmeier, A. and Tomlinson, P.R. (2019). Industrial policy back on the agenda: putting industrial policy in its place? *Cambridge Journal of Regions, Economy and Society*, *12*(3), 319–26.

Bailey, D., Pitelis, C. and Tomlinson, P.R. (2020). Strategic management and regional industrial strategy: cross-fertilization to mutual advantage. *Regional Studies*, *54*(5), 647–59.

Benedettini, O., Neely, A. and Swink, M. (2015). Why do servitized firms fail? A risk-based explanation. *International Journal of Operations & Production Management*, *35*(6), 946–79.

Bianchi, P. and Labory, S. (2006). From 'old' industrial policy to 'new' industrial development policies. In P. Bianchi and S. Labory (eds), *International Handbook on Industrial Policy* (pp. 3–28). Cheltenham, UK and Northampton, MA, USA: Edward Elgar Publishing.

Bishop, P.C. and Colwell, P.F. (1989, 22 June). Price discrimination and the financial aid process. *Illinois Business Review*.

Björkdahl, J. and Holmén, M. (2013). Business model innovation – the challenges ahead. *International Journal of Product Development*, *18*(3/4), 213–25.

Brax, S.A. (2005). A manufacturer becoming service provider – challenges and a paradox. *Managing Service Quality*, *15*(2), 142–55.

Buckley, P.J., Strange, R., Timmer, M.P. and de Vries, G.J. (2020). Catching-up in the global factory: analysis and policy implications. *Journal of International Business Policy*, *3*(2), 79–106.

Bustinza, O.F., Vendrell-Herrero, F. and Gomes, E. et al. (2018). Product-service innovation and performance: unveiling the complexities. *International Journal of Business Environment*, *10*(2), 95–111.

Cortiñas, M., Chocarro, R. and Elorz, M. (2019). Omni-channel users and omni-channel customers: a segmentation analysis using distribution services. *Spanish Journal of Marketing – ESIC*, *23*(3), 415–36.

Coveri, A., Cozza, C., Nascia, L. and Zanfei, A. (2020). Supply chain contagion and the role of industrial policy. *Journal of Industrial and Business Economics*, *47*(3), 467–82.

Dibb, S. and Simkin, L. (2004). *Marketing Briefs: A Revision and Study Guide* (2nd edition). Oxford: Elsevier Butterworth-Heinemann.

Donio, J., Massari, P. and Passiante, G. (2006). Customer satisfaction and loyalty in a digital environment: an empirical test. *Journal of Consumer Marketing*, *23*(7), 445–57.

Drake, M. (2005). Price discrimination notes. *Economic Decision Analysis*, *623*, 1–12.

Duguay, C.R., Landry, S. and Pasin, F. (1997). From mass production to flexible/agile production. *International Journal of Operations & Production Management*, *17*(12), 1183–95.

Ekelund, R.B. (1970). Price discrimination and product differentiation in economic theory: an early analysis. *The Quarterly Journal of Economics*, *84*(2), 268–78.

Farrell, O.C. and Hartline, M.D. (2008). *Marketing Strategy* (4th edition). Mason, OH: Thomson South-Western.

Fogliatto, F.S., Da Silveira, G.J.C. and Borenstein, D. (2012). The mass customization decade: an updated review of the literature. *International Journal of Production Economics*, *138*(1), 14–25.

Frank, A.G., Mendes, G.H.S., Ayala, N.F. and Ghezzi, A. (2019). Servitization and Industry 4.0 convergence in the digital transformation of product firms: a business model innovation perspective. *Technological Forecasting and Social Change*, *141*, 341–51.

Gomes, E., Lehman, D.W., Vendrell-Herrero, F. and Bustinza, O.F. (2021). A history-based framework of servitization and deservitization. *International Journal of Operations & Production Management*, *41*(5), 723–45.
Grundey, D. and Griesiene, I. (2011). Price discrimination: a comparative study of business universities in Lithuania. *Economics and Sociology*, *4*(1), 64–77.
Grundy, T. (2006). Rethinking and reinventing Michael Porter's five forces model. *Strategic Change*, *15*(5), 213–29.
Hara, T., Sato, K. and Arai, T. (2016). Modeling the transition to a provider–customer relationship in servitization for expansion of customer activity cycles. *CIRP Annals – Manufacturing Technology*, *65*(1), 173–6.
Hefley, B. and Murphy, W. (2008). *Service Science, Management and Engineering: Education for the 21st Century*. New York: Springer Science & Business Media.
Hojnik, J. (2016). The servitization of industry: EU law implications and challenges. *Common Market Law Review*, *53*(6), 1575–623.
Hu, S.J. (2013). Evolving paradigms of manufacturing: from mass production to mass customization and personalization. *Procedia CIRP*, *7*, 3–8.
Jenkinson, A. (2009). What happened to strategic segmentation. *Journal of Direct, Data and Digital Marketing Practice*, *11*(2), 124–39.
Jovanovic, M., Sjödin, D. and Parida, V. (2021). Co-evolution of platform architecture, platform services, and platform governance: expanding the platform value of industrial digital platforms. *Technovation*, Article 102218, https://doi.org/10.1016/j.technovation.2020.102218.
Kowalkowski, C., Windahl, C., Kindström, D. and Gebauer, H. (2015). What service transition? Rethinking established assumptions about manufacturers' service-led growth strategies. *Industrial Marketing Management*, *45*(1), 59–69.
Küçük, S.Ü. (2020). *Consumer Voice: The Democratization of Consumption Markets in the Digital Age*. London: Palgrave Macmillan.
Labory, S. and Bianchi, P. (2021). Regional industrial policy in times of big disruption: building dynamic capabilities in regions. *Regional Studies*, *55*(10–11), 1829–38.
Lafuente, E., Vaillant, Y. and Vendrell-Herrero, F. (2019). Territorial servitization and the manufacturing renaissance in knowledge-based economies. *Regional Studies*, 53(3), 313–19.
Lancaster, G. and Withey, F. (2007). *Marketing Fundamentals 2006–2007*. London: Routledge.
Lavoie, N. and Liu, Q. (2007). Pricing-to-market: price discrimination or product differentiation? *American Journal of Agricultural Economics*, *89*(3), 571–81.
Lee, S., Yoo, S. and Kim, D. (2016). When is servitization a profitable competitive strategy? *International Journal of Production Economics*, *173*, 43–53.
Luoto, S., Brax, S.A. and Kohtamäki, M. (2017). Critical meta-analysis of servitization research: constructing a model-narrative to reveal paradigmatic assumptions. *Industrial Marketing Management*, *60*, 89–100.
Mankiw, N.G., Quah, E. and Wilson, P. (2009). *Principles of Economics*. Mason, OH: South-Western Cengage Learning.
Martin, P.C.G., Schroeder, A. and Bigdeli, A.Z. (2019). The value architecture of servitization: expanding the research scope. *Journal of Business Research*, *104*, 438–49.
Matyushok, V., Krasavina, V., Berezin, A. and García, J.S. (2021). The global economy in technological transformation conditions: a review of modern trends. *Economic Research – Ekonomska Istrazivanja*, *34*(1), 1471–97.
Meier, H., Roy, R. and Seliger, G. (2010). Industrial product-service systems – IPS^2. *CIRP Annals – Manufacturing Technology*, *59*(2), 607–27.
Opazo-Basáez, M., Cantín, L.N. and Campos, J.A. (2020). Does distance really matter? Assessing the impact of KIBS proximity on firms' servitization capacity: evidence from the Basque Country. *Investigaciones Regionales*, No. 48, 51–68.
Opazo-Basáez, M., Vendrell-Herrero, F. and Bustinza, O.F. (2018). Uncovering productivity gains of digital and green servitization: implications from the automotive industry. *Sustainability*, *10*(5), Article 1524.
Opazo-Basáez, M., Vendrell-Herrero, F. and Bustinza, O.F. (2019). Talent for services: how gaining access to talent enables successful servitization. In Y. Liu (ed.), *Research Handbook of International*

Talent Management (pp. 35–59). Cheltenham, UK and Northampton, MA, USA: Edward Elgar Publishing.
Opazo-Basáez, M., Vendrell-Herrero, F. and Bustinza, O.F. (2022). Digital service innovation: a paradigm shift in technological innovation. *Journal of Service Management*, *33*(1), 97–120.
Organisation for Economic Co-operation and Development (OECD) (2003). *Glossary of Industrial Organisation Economics and Competition Law*. Compiled by R.S. Khemani and D.M. Shapiro. Commissioned by the Directorate for Financial, Fiscal and Enterprise Affairs, OECD.
Phlips, L. (1983). *The Economics of Price Discrimination*. Cambridge, UK: Cambridge University Press.
Pistoni, A. and Songini, L. (2017). Servitization strategy: key features and implementation issues. *Studies in Managerial and Financial Accounting*, *32*, 37–110.
Porter, M.E. (1997). Competitive strategy. *Measuring Business Excellence*, *1*(2), 12–17.
Porter, M.E. (2008). The five competitive forces that shape strategy. *Harvard Business Review*, *86*(1), 78–93.
Qi, Y., Mao, Z., Zhang, M. and Guo, H. (2020). Manufacturing practices and servitization: the role of mass customization and product innovation capabilities. *International Journal of Production Economics*, *228*, Article 107747.
Rabetino, R., Kohtamäki, M., Brax, S.A. and Sihvonen, J. (2021). The tribes in the field of servitization: discovering latent streams across 30 years of research. *Industrial Marketing Management*, *95*, 70–84.
Rabetino, R., Kohtamäki, M. and Gebauer, H. (2017). Strategy map of servitization. *International Journal of Production Economics*, *192*, 144–56.
Raddats, C., Baines, T. and Burton, J. et al. (2016). Motivations for servitization: the impact of product complexity. *International Journal of Operations & Production Management*, *36*(5), 572–91.
Raddats, C., Kowalkowski, C. and Benedettini, O. (2019). Servitization: a contemporary thematic review of four major research streams. *Industrial Marketing Management*, *83*, 207–23.
Rajala, R., Brax, S.A., Virtanen, A. and Salonen, A. (2019). The next phase in servitization: transforming integrated solutions into modular solutions. *International Journal of Operations & Production Management*, *39*(5), 630–57.
Ranjbari, M., Morales-Alonso, G. and Carrasco-Gallego, R. (2018). Conceptualizing the sharing economy through presenting a comprehensive framework. *Sustainability*, *10*(7), Article 2336.
Sabel, C. and Zeitlin, J. (1985). Historical alternatives to mass production: politics, markets and technology in nineteenth-century industrialization. *Past and Present*, *108*(1), 133–76.
Solomon, S.J. and Mathias, B.D. (2020). The artisans' dilemma: artisan entrepreneurship and the challenge of firm growth. *Journal of Business Venturing*, *35*(5), Article 106044.
Sousa, R. and da Silveira, G.J.C. (2019). The relationship between servitization and product customization strategies. *International Journal of Operations & Production Management*, *39*(3), 454–74.
Spring, M. and Araujo, L. (2013). Beyond the service factory: service innovation in manufacturing supply networks. *Industrial Marketing Management*, *42*(1), 59–70.
Stole, L.A. (2007). Price discrimination and competition. In M. Armstrong and R. Porter (eds), *Handbook of Industrial Organization*, *Volume 3* (pp. 2221–99). Amsterdam: North-Holland.
Tian, J., Coreynen, W., Matthyssens, P. and Shen, L. (2022). Platform-based servitization and business model adaptation by established manufacturers. *Technovation*, Article 102222, https://doi.org/10.1016/j.technovation.2021.102222.
Tomlinson, P.R. (2010). Co-operative ties and innovation: some new evidence for UK manufacturing. *Research Policy*, *39*(6), 762–75.
Valtakoski, A. (2017). Explaining servitization failure and deservitization: a knowledge-based perspective. *Industrial Marketing Management*, *60*, 138–50.
Vandermerwe, S. and Rada, J. (1988). Servitization of business: adding value by adding services. *European Management Journal*, *6*(4), 314–24.
Vendrell-Herrero, F., Bustinza, O.F. and Opazo-Basáez, M. (2021). Information technologies and product-service innovation: the moderating role of service R&D team structure. *Journal of Business Research*, *128*, 673–87.
Vendrell-Herrero, F., Gomes, E., Opazo-Basáez, M. and Bustinza, O.F. (2021). Knowledge acquisition throughout the lifecycle: product and industry learning frameworks. *Journal of Knowledge Management*, *1*, 1–15.

Vendrell-Herrero, F., Parry, G., Opazo-Basáez, M. and Sanchez-Montesinos, F.J. (2018). Does business model experimentation in dynamic contexts enhance value capture? *International Journal of Business Environment*, *10*(1), 14–34.
Vendrell-Herrero, F. and Wilson, J.R. (2017). Servitization for territorial competitiveness: taxonomy and research agenda. *Competitiveness Review*, *27*(1), 2–11.
Visnjic Kastalli, I. and Van Looy, B. (2013). Servitization: disentangling the impact of service business model innovation on manufacturing firm performance. *Journal of Operations Management*, *31*(4), 169–80.
Wang, X., Xie, C., Gao, X. and Wang, S. (2020). Price war countermeasures of cloud manufacturing service platform based on game theory. *Industrial Engineering Journal*, *23*(1), 53–8 [in Chinese].
Wang, Y., Ma, H.-S., Yang, J.-H. and Wang, K.-S. (2017). Industry 4.0: a way from mass customization to mass personalization production. *Advances in Manufacturing*, *5*(4), 311–20.
Zabihi, H., Habib, F. and Mirsaeedie, L. (2013). Definitions, concepts and new directions in industrialized building systems (IBS). *KSCE Journal of Civil Engineering*, *17*(6), 1199–205.

CHAPTER 5. COMPENDIUM ARTICLE 2

Chapter 5, Compendium article 2

Assessing the impact of digital service innovation (DSI) on business performance: the mediating effect of Artificial Intelligence (AI)

Reference: Monroy-Osorio, J. C. (2024). Assessing the impact of digital service innovation (DSI) on business performance: the mediating effect of Artificial Intelligence (AI). *Journal of Enterprise Information Management*.

https://doi.org/10.1108/JEIM-02-2024-0095

Abstract

Purpose: The research aims to explore the dynamic relationship between digital service innovation (DSI), artificial intelligence (AI) and business performance (BPer) in service-based models with a focus on how AI-enhanced insights from service use and customer feedback can strengthen business strategies. The aims are to show that DSI and AI are key to driving growth and efficiency in the digital economy and to underscore AI's role in utilizing contextual data to improve decision-making and business outcomes.

Design/methodology/approach: The study uses general structural equation modeling to analyze Spanish manufacturing firms, focusing on medium-sized enterprises and including both business-to-business and business-to-consumer orientations. Data are drawn from the Iberian Balance Analysis System [Sistema de Análisis de Balances Ibéricos (SABI)] database, complemented by a Qualtrics survey to assess the integration of AI in decision-making processes. The methodology is designed to evaluate the interplay between DSI, AI and BPer, with the aim of identifying actionable insights for service-based business orientations.

Findings: The study clarifies the relationships between DSI, AI and BPer, providing new theoretical and empirical insights. The findings confirm DSI's direct positive impact on performance and suggest AI's nuanced mediating role, emphasizing the need for strategic DSI-AI integration in manufacturing firms for enhanced performance.

Journal of Enterprise Information Management

Assessing the impact of digital service innovation (DSI) on business performance: the mediating effect of Artificial Intelligence (AI)

Received 20 February 2024
Revised 30 May 2024
30 August 2024
Accepted 11 September 2024

Juan Carlos Monroy-Osorio
Department of Marketing and Innovation, School of Management, EAFIT University, Medellin, Colombia and Department of Management, Deusto Business School, University of Deusto, Bilbao, Spain

Abstract

Purpose – The research aims to explore the dynamic relationship between digital service innovation (DSI), artificial intelligence (AI) and business performance (BPer) in service-based models with a focus on how AI-enhanced insights from service use and customer feedback can strengthen business strategies. The aims are to show that DSI and AI are key to driving growth and efficiency in the digital economy and to underscore AI's role in utilizing contextual data to improve decision-making and business outcomes.

Design/methodology/approach – The study uses general structural equation modeling to analyze Spanish manufacturing firms, focusing on medium-sized enterprises and including both business-to-business and business-to-consumer orientations. Data are drawn from the Iberian Balance Analysis System [Sistema de Análisis de Balances Ibéricos (SABI)] database, complemented by a Qualtrics survey to assess the integration of AI in decision-making processes. The methodology is designed to evaluate the interplay between DSI, AI and BPer, with the aim of identifying actionable insights for service-based business orientations.

Findings – The study clarifies the relationships between DSI, AI and BPer, providing new theoretical and empirical insights. The findings confirm DSI's direct positive impact on performance and suggest AI's nuanced mediating role, emphasizing the need for strategic DSI-AI integration in manufacturing firms for enhanced performance.

Research limitations/implications – The research explains the synergistic bond between DSI and AI in boosting BPer and discovering how by-product data can be transformed into strategic insights.

Practical implications – This study advises manufacturing sector leaders to integrate DSI and AI for enhanced performance and competitive advantage, emphasizing the value of high-quality, contextual data for AI learning and decision-making.

Originality/value – Researchers will observe that the study confirms the positive impact of DSI on BPer, while also highlighting the significant role of AI in enhancing this effect.

Keywords DSI, AI, Business performance, B2B, B2C, By-product data, Customer usage data, Customer feedback data

Paper type Research paper

1. Introduction

The integration of digital service innovation (DSI) and artificial intelligence (AI) is rewriting the setting of business strategies, emphasizing the transformative role that technology has in the advancing of service innovation (Enholm *et al.*, 2022; Opazo-Basáez *et al.*, 2022). This renovation is primarily characterized by shifts in service offerings, processes and ecosystems, driven by the strategic utilization of data collected and usage strategies

The author is extremely thankful to the editor and reviewers for providing valuable inputs/suggestions on the paper.

Journal of Enterprise Information Management

1741-0398
DOI 10.1108/JEIM-02-2024-0095

(Benzidia *et al.*, 2021). In this context, by-product information data are often generated inadvertently during customer interactions and routine operations. The data are characterized by its unintentional creation during regular business activities, remain a largely untapped resource with the potential to substantially inform business decisions (Opresnik and Taisch, 2015; Sheng *et al.*, 2017; Sorescu, 2017). Despite its potential, academic literature has yet to fully explore the integration of data within DSI contexts, particularly in terms of AI technology's capability to process and leverage data for enhanced decision-making (Kowalkowski *et al.*, 2023; Raddats *et al.*, 2022).

In this context, the ground-basis provided by Organizational Information Processing Theory (OIPT) serves as a robust theoretical framework for understanding how data can and should be utilized in firms' contexts. It proposes that effectively harnessing contextual data, (such as by-product data through AI tools) can bring insights for business strategies and operational efficiency (DeCanio and Watkins, 1998; S. Sun *et al.*, 2018). Traditionally considered as mere operational residue, this data can be recognized for its potential to predict customer behavior (Benzidia *et al.*, 2021; Kowalczyk and Buxmann, 2014a, b) and optimize inventory management due to its value in contextual information (Sheng *et al.*, 2017; Wamba *et al.*, 2017). The insights derived can influence marketing and business strategies and improve customer engagement, showcasing the practical benefits of applying OIPT (Gallo *et al.*, 2023). Subsequently, the theory suggests that aligning the organizational structure to better manage and interpret complex data flows can significantly enhance decision-making processes and overall business effectiveness (Kowalczyk and Buxmann, 2014b).

A notable example of this phenomenon can be found in the digital streaming sector. Online platforms employ AI to analyze viewer data—not originally collected for strategic use—to tailor content recommendations and optimize streaming quality, thereby enhancing user experience and service offerings (Miller *et al.*, 2019; Vendrell-Herrero *et al.*, 2022). This approach not only impacts business performance (BPer) and customer satisfaction but also illustrates how businesses can leverage advanced technologies to refine decision-making processes and foster growth in a dynamic digital economy, enriching the ongoing discourse on the strategic integration of robust technological frameworks in business strategy development (Bustinza *et al.*, 2020). Moreover, the adoption of advanced technologies, such as IoT, intelligent automation and electronic sensors, are encouraging a dynamic overhaul of traditional service systems, fostering a business orientation that prioritizes continuous adaptation and innovation, based on detailed customer usage analytics (Paiola *et al.*, 2021; Wasim *et al.*, 2024). Conclusively, these integrations of technological advancements, such as AI, serve as a foundational element in reinforcing DSI within competitive business environments (Opazo-Basáez *et al.*, 2022).

Parallel to this effort, firms that navigate though technological integrations are compelled to align their organizational learning and strategies with the demands of modern business environments (Marić *et al.*, 2024; Rabetino *et al.*, 2023). The strategic significance of DSI, coupled with AI's capacity to process and apply by-product data effectively, highlights a shift towards service models that are more personalized, efficient and competitive in the digital ecosystem of a firm and a market (Sjödin *et al.*, 2020). Following these transitions require a deep realignment within digital ecosystems and highlight the need for businesses to adapt their models and technologies to thrive in a digital transformation (Marić *et al.*, 2024). Thus, connecting the principles of OIPT, with the synergy between DSI and AI, can accelerate the development of solutions attuned to real-time customer needs and propels a strategic advancement of business practices, enabling the creation of smarter service models through predictive and prescriptive analytics (Gallo *et al.*, 2023).

As companies integrate AI technology, the transformation of portfolios and service offerings into more personalized, efficient and competitive solutions underscores AI's role as an asset that can capture valuable data from sources not directly related to BPer. This enables data-driven insights and automation to meet the demands of the digital landscape (Bosse *et al.*, 2023; Huang and Rust, 2018). Therefore, a shift towards recognizing AI's critical role in redefining business strategies is essential for enabling data-driven insights and automation, which are necessary to meet the demands of the digital age (Haenlein and Kaplan, 2019).

Such transition requires strategic realignment, as AI technologies can only be effective if trained with sufficient data that enables the identification and anticipation of key requirements beyond traditional BPer indicators (Dubey *et al.*, 2020; Gallo *et al.*, 2023). Therefore, a gap in the academic literature emerges, particularly where DSI involves strategies linked to contextual consumer information, such as the use of digital services and subsequent feedback. This feature correlates with BPer, an area previously explored in research studies (Jovanovic *et al.*, 2021; Rabetino *et al.*, 2023). The relationship revealed through the lens of OIPT between DSI and BPer—when mediated by advanced technologies like AI trained with by-product data from customer usage and feedback—highlights a direct connection to consumers and, consequently, offers a significant market advantage (Narvaiza *et al.*, 2023).

The current research addresses this gap by analyzing the proposed relationship in a sample of 354 firms in Spain. The objective of the study is to elucidate the relationship between DSI and BPer, emphasizing the mediating role of AI technologies. Additionally, the analysis offers insights to organizations embracing DSI strategies by harnessing the value of data created by two main strings of data collection: data on customer use and data on customer feedback. Furthermore, this research extends the academic literature by illustrating how DSI, underpinned by the robust theoretical construct of OIPT, can improve by-product data to a strategic resource within the digital economy, thus providing practical insights, positioning DSI, AI and by-product data analysis as elements for advancing business outcomes.

2. Literature review

2.1 DSI and business performance: an OIPT perspective

DSI has become a remarkable factor in areas of big impact as a performance of businesses, especially within the manufacturing sector where its effect is most pronounced (Opazo-Basáez *et al.*, 2022). Existing literature underscores the role of DSI in developing comprehensive business-focused digital service frameworks (Bustinza *et al.*, 2018; Rabetino *et al.*, 2023) and can aid as tools for addressing the complexities of digital transformation (Manser Payne *et al.*, 2021). Nonetheless, when these frameworks are seen through a theoretical lens as the OIPT viewpoint, it can follow structural questions to the increased demands for information processing that digitalization imposes on organizations. According to OIPT, the alignment of an organization's structure with its information processing needs is crucial for efficient decision-making and effective task performance (Egelhoff, 1991; Kowalczyk and Buxmann, 2014a, b). Thus, the structured approaches suggested by these theory frameworks are not merely technological-strategy-oriented upgrades, since they deliberately align technological advancements with core business objectives such as strategy, operations and customer relations (Sun *et al.*, 2018; Verhoef *et al.*, 2021).

Following this, a strategic decision-making system can incorporate both individual and organizational information processing, which requires a dual-level approach to understanding choices inside firms (Rogers *et al.*, 1999). This integration is further elaborated in recent studies that explore the role of big data and analytics in enhancing organizational decision-making (Benzidia *et al.*, 2021; Soni *et al.*, 2023). It is in this context that DSI can offer differentiation by facilitating the collection of contextual data, providing a richer understanding of operational and strategic challenges, rather than relying solely on correlational data related to objectives (Brocke *et al.*, 2016; Vendrell-Herrero *et al.*, 2018). By harnessing the contextual-type of data, it allows businesses to gather and analyze situational information that goes beyond correlations. In the context of servitization and digital servitization, where businesses shift from a product-centric to a service-centric model enhanced by digital technologies (Vendrell-Herrero *et al.*, 2023; Kohtamäki *et al.*, 2020), the use of AI can significantly amplify the impact of these strategies. By integrating AI into DSI, companies can process vast amounts of contextual data—such as customer behavior, operational conditions and market trends—to tailor their services more precisely to the needs of their customers (Gebauer *et al.*, 2021). AI-driven insights, derived from contextual data, can enable businesses to offer more personalized and adaptive services, thereby enhancing customer use and satisfaction therefore enhancing BPer (Lenka *et al.*, 2016). In this way, a DSI strategy that leverages AI not only supports the creation of innovative digital services but also ensures that these services are highly relevant and responsive to the dynamic environments in which they are deployed.

Overall, this approach is in line with the OIPT, which addresses the complexities of managing extensive and often nuanced information within an organization leading to an integration that can underscore the relevance of DSI and OIPT in on-going strategic decision-making (Burton *et al.*, 2023; Sjödin *et al.*, 2020). By integrating DSI with OIPT, it ensures a comprehensive understanding of market dynamics and consumer behavior, thereby enriching strategic decision-making processes and improving overall BPer (Kowalczyk and Buxmann, 2014a; Marcon *et al.*, 2022; Opazo-Basáez *et al.*, 2022). For example, in the telecom sector, AI-powered chatbots analyze customer interaction data in order to offer personalized services and improve operational efficiency, demonstrating how AI can streamline traditional service models into more efficient, customer-focused solutions (Bustinza *et al.*, 2022; Dalenogare *et al.*, 2023). This methodology illustrates the practical application of DSI and OIPT, highlighting the importance of integrating both frameworks to leverage advanced data utilization for strategic decision-making and BPer improvement (Brocke *et al.*, 2016; Opazo-Basáez *et al.*, 2024a, b).

Nonetheless, DSI, as a novel framework that integrates technology and services, risks focusing solely on tangible benefits, such as BPer while overlooking the valuable market and consumer insights (Raddats *et al.*, 2022). The transition facilitated by DSI includes the development of new components in service portfolios, allowing businesses to offer distinctive and innovative service options (Narvaiza *et al.*, 2023; Soto Setzke *et al.*, 2023). Technologies such as IoT, cloud computing and AI enable companies to enhance their service delivery, which is essential for maintaining customer satisfaction and support (Marcon *et al.*, 2022). Additionally, the use of by-product data, information generated during regular operations but not traditionally utilized for decision-making, represents a critical aspect of this transition (Wirtz *et al.*, 2021). Analyzing this data can discover patterns and insights that conventional process collection methods might overlook, aiding firms in anticipating customer needs and refining operational efficiencies (Opazo-Basáez *et al.*, 2024a, b). These enhancements in strategic decision-making are grounded in OIPT, which emphasizes the importance of aligning information processing with organizational objectives to maintain relevance and efficiency in the digital era (Kowalczyk and Buxmann, 2014a, b; Rogers *et al.*, 1999). Therefore, integrating DSI with OIPT not enhances BPer but also broadens the understanding of market dynamics and consumer behavior through comprehensive data utilization, including by-product data, thus, enriching strategic decision-making processes.

2.2 AI and service-based competitiveness

Previous literature on AI and BPer suggests a significant shift in enhancing service business competitiveness and rethinking businesses and strategies (Bosse *et al.*, 2023; Madanaguli *et al.*, 2024). AI influence is particularly notable in the service-based business ecosystem, where it integrates service-oriented solutions with business innovation and performance goals (Huang and Rust, 2018). This transformation has impacted business practices by enhancing customer experiences, optimizing operational efficiencies and reshaping stakeholder relationships (Enholm *et al.*, 2022). However, it also presents significant challenges, including potential biases in AI decision-making (Gallo *et al.*, 2023; Sjödin *et al.*, 2023). Preconceptions can stem from various sources, such as biased training data or flawed algorithms, leading to unfair or disadvantageous outcomes (Bag *et al.*, 2021; Mikalef and Gupta, 2021). For instance, AI systems used in customer service chatbots can inadvertently favor certain customer profiles over others, potentially leading to unequal treatment and customer dissatisfaction (Enholm *et al.*, 2022). Therefore, while AI, when connected with a DSI service strategy, can offer substantial benefits for company performance, addressing these challenges is necessary to ensure equitable and responsible technological adoption (Wamba-Taguimdje *et al.*, 2020).

In addition, digitalization in service strategies is enhanced by AI, bridging the gap between traditional service methods and innovative, efficient and personalized digital services (Payne *et al.*, 2021). AI predictive capabilities in maintenance and support can simplify resource allocation and reduce downtimes, leading to cost savings and increased reliability (Bosse *et al.*, 2023). This transformation aligns with the principles of DSI, which seeks to harness digital technologies to transform service delivery (Enholm *et al.*, 2022). Efficiency, a cornerstone of this shift, is redefined through AI, which optimizes processes and resources, reducing waste and increasing productivity (Qi *et al.*, 2023). This optimization is essential in a rapidly evolving business environment, where adapting and responding to market changes quickly is a competitive advantage (Gallo *et al.*, 2023). Nonetheless, the non-strategic use of assessments derived from information not connected with the entire value chain of the company will result in biased decisions and loss of competitive value (Bustinza *et al.*, 2018; Kohtamäki *et al.*, 2022).

As an example, companies like Amazon apply AI-driven analytics to enhance both customer experience and operational efficiency. Amazon employs AI algorithms to analyze by-product data from customer interactions, such as browsing history, purchase patterns and product reviews, to provide personalized recommendations and anticipate customer needs (Ritala *et al.*, 2014). This data-driven approach not only improves customer satisfaction by offering tailored shopping experiences but also optimizes inventory management by predicting demand trends and reducing stockouts. Additionally, AI-powered chatbots and virtual assistants handle customer inquiries and support, providing timely and accurate responses while freeing up human resources for more complex tasks (Shankar, 2018). These applications display how integrating DSI with OIPT can leverage by-product data to create efficient, customer-focused solutions that enhance BPer (Soto Setzke *et al.*, 2023).

The use of AI as a tool for strategic differentiation offers further benefits for enhancing DSI (Opazo Basáez *et al.*, 2024). Several research emphasize the significant role of AI in an increasingly digital and interconnected environment, identifying it as a fundamental driver of transformation that aligns service delivery with the demands of the digital age (Marić *et al.*, 2024; Rabetino *et al.*, 2023). This shift pushes towards a complex, customer-centric model (Kowalkowski *et al.*, 2023). However, this presents complex challenges, including debates about AI self-learning capabilities and how businesses often use AI with insufficient valuable data for training and evolving better decision-making processes (Bosse *et al.*, 2023; Haenlein and Kaplan, 2019). Moreover, there is a perception that AI offers immediate solutions, often viewed as a fast solution, without acknowledging the necessity for continuous training and a steady flow of information required for making increasingly accurate decisions (Enholm *et al.*, 2022; Xiong *et al.*, 2020). Addressing these challenges is decisive to ensuring that AI-enhanced DSI for the purpose of BPer and also to maintain responsible and equitable use of technology.

Navigating towards an AI-driven, service-oriented future demands continuous innovation and adaptability and requires commitments in order to align technological advancements with human values and societal needs (Lehner *et al.*, 2022; Loureiro *et al.*, 2021). Integrating AI into service business strategies is indispensable, not merely as a competitive strategy but as a requirement from the market (Abou-Foul *et al.*, 2023). Integration efforts within the DSI emphasize that advancing through AI in the service ecosystem is more than just technological adoption; but restructuring business models to foster a more responsive, customer and market-focused service paradigm as well (Lehner *et al.*, 2022). This approach is necessary to harness the full potential of AI and DSI in driving BPer and strategic growth.

2.3 Data as a by-product in service contexts: an OIPT view

In the developing landscape of the service industry, data generated as by-products of various business processes have emerged as an asset that drives innovation and efficiency (Opresnik and Taisch, 2015, Porter and Heppelmann, 2016). By-product data, often overlooked in traditional business models, business-to-business (B2B) and business-to-consumer (B2C), have gained prominence in the digital landscape, where every interaction and transaction can be traceable by digital imprints (Quarteroni *et al.*, 2013). Consequently, it has prompted a re-evaluation of data, transforming perceptions from mere operational residue to strategic assets (Ranjan and Foropon, 2021). The value of this data is not limited to its volume; it also encompasses its potential for insightful pattern recognition, predictive analytics and a deep understanding of customer behavior (Demchenko *et al.*, 2013). For instance, data from customer interactions on digital platforms can provide remarkable insights into consumer preferences, enabling businesses to tailor their offerings with precision. Similarly, operational data from manufacturing processes can lead to substantial improvements in efficiency and significant reductions in resource wastage (Kowalczyk and Buxmann, 2014a, b; Kowalkowski *et al.*, 2023).

Additionally, the shift toward a data-centric approach is revolutionizing the service ecosystem, emphasizing the potential of by-product data in business models as a catalyst for innovation and a source of competitive advantage (Dubey *et al.*, 2020; Wamba *et al.*, 2017). The usage of by-product data aligns with the emerging trend of servitization, where businesses transition from a product-centric to a service-oriented model. This shift underscores the role of data as a primary enabler in delivering enhanced services (Quarteroni *et al.*, 2013). For example, in manufacturing sectors, transitioning to service-oriented models are facilitated by leveraging data generated from product use and it allows innovative services such as predictive maintenance and automated real-time customer satisfaction and loyalty strategies (Opresnik and Taisch, 2015; Porter and Heppelmann, 2016). In digital services, by-product data becomes influential in creating personalized user experiences, critical for customer engagement and retention (Cenamor *et al.*, 2017). Nevertheless, this data exploitation also raises ethical considerations and necessitates robust data governance frameworks to ensure privacy and ethical use (Lehner *et al.*, 2022). Consequently, balancing data utilization for business growth with consumer data privacy remains a central challenge in maximizing the value of by-product data in the service ecosystem.

As a result, from an OIPT perspective, these approaches elucidate how organizations adjust their structures and processes to better align with information processing needs, thus, managing uncertainty and complexity effectively (Carlos Monroy-Osorio *et al.*, 2023; Yuan *et al.*, 2023). By integrating these insights, firms can enhance their decision-making capabilities and will be able to strategically position themselves to leverage information as a dynamic asset (Cenamor *et al.*, 2017). The incorporation of by-product data into service strategies exemplifies the practical application of OIPT, as organizations transform these data streams into actionable intelligence, supporting both strategic and operational objectives. This, in turn, underscores how the efficient processing and utilization of by-product data, guided by OIPT principles and enhances organizational agility and competitive positioning in a rapidly evolving digital landscape.

2.3.1 DSI–AI and customer use data. The integration of DSI, enabled by AI in B2B markets, signals a shift from traditional operational models to those centered on customer use (Kowalkowski *et al.*, 2023). This transition, driven by the strategic use of by-product data, reflects an evolution in the approach to understanding and responding to customer needs (Paschen *et al.*, 2019). AI's analytical capabilities allow businesses to describe and interpret customer-generated data, thereby enhancing the understanding of customer behavior, preferences and future requirements. Such an approach positions AI beyond its operational role, establishing it as a central component in fostering a continuous learning loop (Bag *et al.*, 2021; Biemans and Griffin, 2018). Iterative engagement with customer data uncovers patterns and trends, providing insights essential for strategic decision-making (Bonamigo *et al.*, 2022). This model signifies a considerable advancement in service innovation and customization within the B2B sector, where customer interaction data drives service improvements. AI algorithms, proficient in analyzing extensive datasets, play a critical role in converting data into actionable business intelligence, adapting continuously to customer needs and market dynamics (Hübner *et al.*, 2018).

Focusing on learning from customer use within the B2B sector underscores the dynamic nature of service delivery. In the contemporary service strategy ecosystem, by-product data derived from customer interactions has become a crucial factor in the evolution of service models (Hübner *et al.*, 2018; Paschen *et al.*, 2019). This data, enriched with insights from customer engagement, moves companies beyond traditional financial and performance indicators, facilitating a shift toward more dynamic and responsive models (Kowalkowski *et al.*, 2023). Such transformation ensures that services not only align with current customer needs but also possess the agility to anticipate and adapt to evolving market demands and consumer preferences (Hübner *et al.*, 2018). The strategic application of AI in analyzing this by-product data represents a significant shift for companies (Eriksson and Heikkilä, 2023), enabling a move from traditionally reactive approaches to more proactive and forward-thinking strategies. AI-driven predictive analytics empower companies to design services that are not merely responsive to immediate needs but also anticipatory, preempting future customer requirements (Raddats and Easingwood, 2010). Thus, an AI-enabled strategy supports the development of service models that are both adaptive to current demands and predictive of future trends, ensuring long-term relevance in a competitive and rapidly changing business environment (Peltier *et al.*, 2023).

2.3.2 DSI–AI and customer feedback data. The incorporation of by-product data derived from customer feedback into AI applications within B2C contexts (i.e. in front-office operations in manufacturing firms), highlights the critical role of learning from customer interactions (Hallowell, 1996; B. Sun *et al.*, 2006). This approach is crucial across various business models, extending beyond traditional B2C frameworks. AI's transformative role lies in enhancing the understanding of customer needs and preferences, a process driven by the analysis of diverse feedback (Dawes, 2009). The insights gained from this interaction, encompassing both satisfaction and grievances, are instrumental in refining AI algorithms and strategies to better align with customer expectations (Lee *et al.*, 2023). Consequently, AI evolves from a mere efficiency tool into a dynamic agent of customer-centric innovation, strengthening the relationship between businesses and their clients.

Therefore, the strategic significance of learning from customer feedback becomes increasingly evident as businesses transition toward service-focused models. In these models, customer feedback is integral to the ongoing development and refinement of services, ensuring alignment with customer needs and expectations (de Haan *et al.*, 2015; Lee *et al.*, 2023). By-product data from feedback, encompassing both explicit and implicit customer sentiments, provides a valuable resource for refining and adapting AI-driven services (Eriksson and Heikkilä, 2023; Sjödin *et al.*, 2021). Accurately interpreting this data, while mitigating potential biases, is essential for evolving services in response to actual customer needs and market trends (Park *et al.*, 2019). The effective utilization of customer feedback in shaping AI applications not only enhances service quality but also strengthens customer relationships, underscoring the role of feedback as a fundamental element in business adaptation and growth (Bosse *et al.*, 2023).

In summary, the convergence of AI-driven, DSI and the strategic use of by-product data marks a paradigm shift in both B2B and B2C business models (Kamp *et al.*, 2023). This shift represents a departure from conventional service delivery towards a model where continuous learning, adaptation and customer-centric innovation are paramount. By leveraging AI to extract insights from customer usage and feedback data, businesses can consistently refine and evolve their service offerings (Häikiö and Koivumäki, 2016; Vargo *et al.*, 2023). This approach not only enhances the relevance and competitiveness of enterprises but also signals a new era in data-driven service innovation (Zhou *et al.*, 2023). It emphasizes the importance of proactive, informed and adaptive strategies in today's business landscape, where customer insights are crucial for driving service development and innovation.

2.4 Hypotheses development

2.4.1 Digital service innovation and business performance. DSI and digital servitization have emerged as key drivers of BPer in the innovative and competitive landscape (Carlos Monroy-Osorio *et al.*, 2023; Gebauer *et al.*, 2021). Digital servitization integrates technologies into service offerings, enabling firms to transition from traditional product-centric models to service-oriented approaches. This shift enhances service delivery and customer engagement, creating value propositions that meet contemporary market demands (Burton *et al.*, 2023; Kohtamäki *et al.*, 2019). Therefore, the integration of digital technologies allows firms to offer more personalized and efficient services, improving customer satisfaction and operational efficiency (Paiola *et al.*, 2021).

Accordingly, an interplay between digital servitization and DSI has an insightful impact on BPer (Bustinza *et al.*, 2018; Martín-Peña *et al.*, 2019), where digital platforms facilitate real-time data exchange and analytics, fostering innovation and agility. By embedding IoT and AI within service frameworks, firms can proactively predict and respond to customer needs, gaining a competitive edge (Huang and Rust, 2018; Paiola *et al.*, 2021). Digital advancements support and enhance servitization efforts and can lead to improved BPer by enabling firms to leverage data-driven insights, optimize resource allocation and develop innovative solutions that cater to evolving customer preferences (Jajja *et al.*, 2017; Wamba-Taguimdje *et al.*, 2020). Therefore, a synergy between DSI and digital servitization enables organizations to harness the full potential of digital transformation, ultimately driving growth and sustaining competitive advantage in dynamic markets (Raddats *et al.*, 2022; Vilkas *et al.*, 2022).

Nonetheless, despite the growing body of qualitative evidence supporting the benefits of DSI and digital servitization, there remains a scarcity of quantitative studies measuring the impact on BPer (Opazo-Basáez *et al.*, 2024a, b). Furthermost, a large number of research has focused on case study evidence, which, while insightful, demands an empirical rigor needed to establish a generalizable understanding of these phenomena. The existing literature often highlights the challenges of quantifying the returns on digital investments, particularly given the complex and multifaceted nature of digital transformation initiatives (Kowalkowski *et al.*, 2023; Raddats *et al.*, 2022). Nonetheless, the strategic implications of DSI are profound, as they necessitate a realignment of business models and organizational structures to fully harness the potential of digital technologies (Rabetino *et al.*, 2023). By empirically validating the relationship between DSI and BPer, researchers can provide valuable insights into how firms can strategically leverage digital innovations to achieve enhanced operational outcomes and customer satisfaction. To address this gap, the following hypothesis is proposed:

H1. DSI exerts a positive influence on a firm's BPer.

This hypothesis aims to empirically validate the theoretical assertion that DSI enhances BPer, thus providing a more robust understanding of how DSI can be leveraged to achieve strategic business objectives.

2.4.2 Role of AI and by-product data in enhancing DSI and business performance. AI serves as a transformative technology within the DSI framework, offering the potential to significantly improve BPer through enhanced data processing and decision-making capabilities (Qiu *et al.*, 2023; Rabetino *et al.*, 2023). Literature in the field supports the notion that technological innovations like AI can mediate the relationship between DSI and BPer by providing essential tools for improved information processing (Huang and Rust, 2018; Sjödin *et al.*, 2023). Moreover, according to OIPT, effective information processing is necessary for managing complexity and uncertainty in business environments (Brocke *et al.*, 2016; Karwatzki *et al.*, 2017).

Consequently, AI can enrich the DSI framework by providing advanced tools for analyzing customer usage and feedback data, which are critical for developing data-driven service innovations (Kowalczyk and Buxmann, 2014a; Wamba *et al.*, 2017). This aligns with the principles of OIPT, emphasizing the importance of cutting-edge information processing in dynamic business contexts (Egelhoff, 1991). Hereafter, an AI capability to handle large volumes of data and produce actionable insights will support proficient information management, facilitating firms to navigate complexity and uncertainty (Sjödin *et al.*, 2023). Moreover, the by-product data, often overlooked in traditional data collection methods, holds the potential to uncover patterns and insights, critical for anticipating customer needs and refining operational efficiencies.

This interactions accentuate the opportunity for AI to enhance the efficiency of DSI initiatives, predominantly in business contexts such as B2B (customer use) and B2C (Customer feedback). In B2B models, customer uses by-product data can be archived due to longer sales cycles and detailed usage patterns, better than feedback data, allowing companies to analyze extensive data on product utilization (S. Sun *et al.*, 2020). Additionally, B2C models benefit from more accessible customer feedback directly connected to end users, providing insights into satisfaction and preferences (Song *et al.*, 2018). It is in this B2C context that contextual and residual data, the by-product data, can be a valuable input for AI training since it is obtained more quickly and with better quality than in B2B environments (Qi *et al.*, 2023; Xie, 2023). Hence, analyzing the mediation effect of AI in the relationship between DSI and BPer, and the role of by-product data in enhancing this relationship, poses the following hypothesis:

H2. AI, enhanced by by-product data from customer use and feedback, has a positive mediation in the relationship between DSI and BPer.

The hypothesis aims to validate the theoretical assertion that AI when combined with by-product data of customer use and feedback, improves the effectiveness of DSI in enhancing BPer. This provides a nuanced understanding of how leveraging overlooked data sources can lead to strategic business advantages. Figure 1 summarizes the conceptual framework.

3. Methodology

3.1 Data collection

The study explores the diverse service strategies of a selection of Spanish manufacturing firms, providing insights into the Spanish industrial landscape characterized by relatively few large corporations and a prevalence of medium-sized enterprises (Opazo-Basáez *et al.*, 2024a, b). The sample includes companies operating both B2B and B2C business models, allowing for differentiation based on their focus on service usage data versus high volumes of feedback data. The principal data source is the Iberian Balance Analysis System [Sistema de Análisis de Balances Ibéricos (SABI)] database, offered by Bureau Van Dijk (BvD) (http://sabi.bvdep.com), which presents an extensive overview of Spain's manufacturing sectors.

Targeting medium-sized enterprises within NAICS codes 31–33, the study encompasses sectors from food, beverage and textile manufacturing (NAICS 31) to the production of non-mineral and mineral products, including hardware and machinery (NAICS 32 and 33), involving a total of 1,504 companies. Data were collected through a Qualtrics survey (https://www.qualtrics.com), adhering to the methodology standards set by Goh and Eldridge (2019). Companies completed a self-administered questionnaire, a strategy proven effective for collecting relevant company data (Cao *et al.*, 2021; Acciarini *et al.*, 2023). The Spanish questionnaire underwent meticulous translation to ensure integrity, following procedures outlined by Marchena Sekli and De La Vega (2021). The survey targeted senior executives of medium-sized manufacturing firms, disseminated via mail and the LinkedIn social media platform. The sample was representative of the wider population in terms of sector and company size. Post-collection, the survey results were integrated with financial data from the SABI database for the year 2022. A non-response bias analysis, comparing participating and non-participating firms using SABI's size, industry and performance data (Armstrong and Overton, 1977), revealed no significant differences, indicating minimal sample bias.

Several measures were taken to assess and minimize common method bias (CMB), acknowledging that most measures were self-reported. To ensure objectivity, dependent and independent variables were measured objectively, reducing susceptibility to CMB as respondents provided factual data about their firm's most recent foreign entry and mode experience. Confirmatory factor analysis (CFA) indicated poor model fit (TLI = 0.318; CFI = 0.394; RMSEA = 0.122), suggesting that CMB was not a significant issue. Factor analysis using principal-component factors retained one factor with an eigenvalue of 3.80704, explaining 63.45% of the variance, with subsequent factors showing a sharp decline in eigenvalues. The loadings indicated strong associations, especially for BPer variables, with factor loadings of 0.8488, 0.8592, 0.8804 and 0.8969, respectively. The likelihood ratio (LR) test confirmed the model's robustness with a chi-square of 1242.64 and a p-value of less than 0.001. These results, including high explained variance and significant factor loadings, corroborate the CFA findings, ensuring the reliability and validity of the measures and mitigating concerns about CMB. Table 1 outlines the data for all surveyed firms.

3.2 Variables

This study adopts measurement techniques established by prior research to guarantee the validity and reliability of the evaluations, utilizing dichotomous questions and five-point Likert-type scales ranging from "1" (strongly disagree) to "5" (strongly agree).

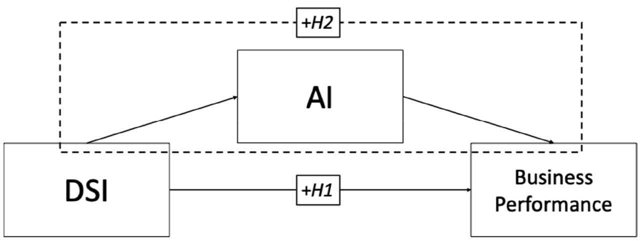

Figure 1.
Conceptual model proposed

The independent variable of DSI employs servitization questions in order to identify the degree of advanced services, focusing on whether companies have implemented advanced services using technology. This is assessed through a dichotomous question, where 0 signifies “no” and 1 signifies “yes,” asking about comprehensive services or business solutions. Examples include consulting services, logistics leasing, subscription payments, research and development (R&D), pay-per-use services, IT support platforms, remote asset monitoring, sensors and data analysis. This question captures the extent to which manufacturing companies provide sophisticated services integrated with technology and digital tools. By assessing the inclusion of advanced, technology-integrated services, the question aligns with the DSI concept that emphasizes the strategic use of digital technologies to remodel service design, delivery and individualization, leading to innovative offerings and improved operations, thereby addressing both strategic and competitive needs in the manufacturing sector (Opazo-Basáez *et al.*, 2022).

The dependent variable of BPer is measured using a modified version of a validated Likert scale developed by Jajja *et al.* (2017), which originally consists of 7 items. To better align with the specific objectives of the research, five key measures were selected: market share, market share growth rate, revenue growth, overall profitability and return on sales. The measures of return on assets and brand acceptance were excluded due to their lesser relevance to the study’s focus on direct financial and market performance outcomes. By applying this tailored version of the validated scale, the study ensures the precision of observable variables essential for constructing the latent construct of BPer. This approach incorporates both financial and market-driven outcomes within a unified evaluative framework, enabling well-informed conclusions that support strategic decision-making.

Finally, the mediation variable aims to measure the utilization of AI within firms. It employs a dichotomous question designed to assess the presence of AI as a critical component. The binary variable is assigned a value of “1” when a firm reports the use of “AI in conjunction with computational intelligence and/or digital analytical tools to support decision-making processes.” By incorporating these elements into the survey through a single, focused question, the research captures the decision of AI integration within the operational environment of the company, ensuring the measure of engagement with AI technology in enhancing its decision-making infrastructure. Following this approach, the study aligns with the definition of AI in business as discussed by Bosse *et al.* (2023), where AI technologies are embedded in business processes to perform traditional tasks handled by workers. In this context, AI refers to technologies that mimic human intelligence through decision trees, if-then rules and learning algorithms, thereby acting autonomously to perceive environmental prompts, make decisions and execute actions. This integration is critical for firms seeking to improve operational efficiency and decision-making processes, as

Variable	Manufacturing firms classified under NAICS 31, 32 and 33
Location	Based in Spain with operations across the European Union
Unit of analysis	Medium-sized businesses employing 50–249 individuals
Total population	1,504 manufacturing firms with a service portfolio
Response rate	354 valid questionnaires received, representing 23.53% of the total population
Data collection method	Structured questionnaire
Type of companies	B2B and B2C
Research conducted	Data collected over a three-month period, from June to August 2022
Respondent	CEO, CMO, COO or equivalent roles
B2B companies	244 firms of the sample
B2C companies	110 firms of the sample

Table 1.
Questionnaire firms’ participants

AI technologies can adapt based on prior stakeholder interactions and continuously evolve to meet business needs (Bosse *et al.*, 2023).

3.3 Empirical design

During the study, an analysis was carried out on response patterns and the distribution of industries within a dataset comprising 1,504 observations. Of the total, 24 observations, which account for 1.6%, were found to be incomplete, whereas 354 observations, representing 23.54% of the dataset, were identified as the actual usable sample of firms using advance services. Additionally, an assessment of employment figures was conducted, revealing a total of 114 employees across different categories: 88 employees were associated with non-responsive cases, 67 with abandoned ones, 56 with cases marked by missing information and 68 corresponded to the sample used in the analysis. The study further delved into the distribution of observations pertaining to three distinct NAICS codes: 31, 32 and 33. It was noted that observations under NAICS code 31 were distributed relatively uniformly across all categories, with the highest incidence of missing information peaking at 33.33%. In contrast, the distribution for NAICS code 32 was more varied, with the most significant proportion, at 42.37%, found in cases that were abandoned. NAICS code 33, on the other hand, demonstrated the most considerable disparity across the categories, with the missing information category capturing the highest share at 39.50% and the abandoned cases category holding the lowest at 24.31%. An analysis of observations relative to the capital country percentage also yielded notable findings, with the highest percentage of non-responses recorded at 36.1% and the lowest percentage of abandoned cases at 24.4%. To provide a clear overview of these findings, Table 2 is included to summarize the universe of observations, offering a detailed breakdown of the industry distribution and response patterns within the study's sample.

3.4 Statistical design

Regarding the statistical approach, generalized structural equation modeling (GSEM) served as the analytical method. Multivariate statistical technique is designed to assess relationships between latent constructs and observed variables simultaneously, providing a detailed analysis of the complex interdependencies within the data (Palmer and Sterne, 2015). GSEM outstandingly accounts for potential measurement errors, thereby providing more accurate estimates of both direct and indirect effects among the variables. This feature is particularly useful in deciphering the complexities inherent in multifaceted datasets. Moreover, GSEM's versatility is evident in its capacity to adapt to various types of response variables, accommodating different distributions. Hence, the statistical model enables a thorough investigation into the nuanced dynamics of DSI, AI and BPer, considering the indicators and potential mediating factors that contribute to the overall model. This method allows for a comprehensive evaluation of the direct and indirect effects within the model, ensuring a detailed and accurate analysis of the relationships between constructs.

	Non-response		Response		Population
	Unanswered	Abandoned	Missing	Actual sample	All
# Observations	672	454	24	354	1,504
# Employees	88	67	56	68	114
% NAICS – 31	29.59%	33.33%	33.21%	33.05%	31.59%
% NAICS – 32	33.33%	42.37%	27.58%	32.50%	35.77%
% NAICS – 33	37.08%	24.31%	39.50%	34.45%	32.65%
% Capital	%36.1	%24.4	%28.7	%35.4	%32.2

Table 2. Distribution of observations in terms of participation and size

4. Data analysis

4.1 Data validation

The data used in this analysis encompass a sample of 354 observations, focusing on various factors influencing BPer. The variables of DSI and AI are binary, indicating the presence or absence of digital service innovation and technological capabilities related to AI. BPer, the primary latent outcome, is represented through ordinal responses, which were analyzed using an ordinal probit model within a GSEM framework. The summary statistics for BPer indicate a mean of approximately zero (−1.10e−08) with a standard deviation of 0.9486 and a range extending from −2.3643 to 1.0309. These statistics suggest that the BPer scores are centered around zero but exhibit considerable variation. To assess the influence of DSI on BPer, with AI as a mediator, an ordinal probit link function was employed within the GSEM model. The results demonstrate that DSI significantly affects AI, with a coefficient of 0.9203 ($p < 0.0001$), suggesting a positive relationship.

Likewise, AI shows a significant positive influence on BPer, with a coefficient of 0.5383 ($p < 0.0001$). These relationships highlight the importance of DSI and AI in enhancing business outcomes. The model includes several thresholds for the ordinal BPer variable, with the first 10 thresholds ranging from −1.8239 to −1.0380, each providing distinct cut-off points that delineate the different levels of BPer. These thresholds are necessary for the ordinal probit model as they define the boundaries between the various categories of the ordinal outcome. The robust standard errors applied in the model account for potential deviations from normality in the distribution of BPer, ensuring the reliability of the parameter estimates. Overall, the analysis underscores the role of DSI and the mediating effect of AI in driving BPer, delivering a positive and statistically significant coefficients, indicating that AI enhances the impact of DSI on BPer. The GSEM approach with an ordinal probit link effectively captures the ordinal nature of BPer, providing nuanced insights into the factors contributing to improved business outcomes. Table 3 summarizes the result of GSEM estimation.

4.2 Confirmation of the relations of DSI and business performance

The data analysis stage focuses on examining the influence of DSI on BPer using a GSEM approach. The analysis unveils a direct effect of DSI on BPer, with a coefficient of 1.060 and a standard error of 0.1010, yielding a z-value of 10.49, which is highly significant ($p < 0.000$). The 95% confidence interval for this direct effect ranges from 0.8619 to 1.2582, with a standardized coefficient of 0.6274, indicating a substantial positive impact of DSI on BPer. Additionally, the model also captures the indirect effects of BPer on five observed variables (BP_V1 to BP_V5). The coefficients for these indirect effects range from 0.9679 to 3.2530, with all corresponding z-values being highly significant, further supporting the robustness of BPer as a mediator between DSI and various aspects of BPer.

Subsequently, the direct effect of DSI on BPer suggests that improvements in DSI will lead to significant enhancements in BPer, validating the H1 proposed. This finding is consistent with the hypothesis that DSI is a critical driver of business success. The standardized coefficient of 0.6274 underscores the importance of DSI in the context of modern business strategies. On the other hand, the indirect effects reveal how BPer, as a latent

Table 3. Results of GSEM with ordinal probit link validation

Parameter	Coefficient	Std. error	z-value	$P>\|z\|$	95% confidence interval
Latent variable: BPer (Business performance)					
DSI	0.9203	0.1283	7.17	0.000	0.6688 to 1.1718
AI	0.5383	0.1310	4.11	0.000	0.2815 to 0.7951

variable, translates into observable business outcomes across different dimensions. The highest standardized coefficient (1.6704) is observed for BP_V5, indicating that this particular aspect of BPeris most strongly influenced by BPer. Meanwhile, BP_V3, with a standardized coefficient of 1.1515, is less impacted, though still significantly affected. These variations highlight the differentiated impact of BPer on various facets of BPer, reflecting the multifaceted nature of business success. Table 4 summarizes the analysis results, providing a comprehensive overview of the findings.

4.3 Confirmation on the mediating effect of AI on the relation between DSI and business performance in by-product data of customer use

The results of the GSEM analysis, primarily in a B2B, reveal a meaningful relationship between DSI, AI and BPer. The direct effect of DSI on BPer is statistically significant, with a coefficient of 0.8231, indicating that firms engaging in higher levels of DSI tend to achieve better BPer. The estimated variance for BPer suggests moderate variability in performance outcomes among the firms, highlighting the potential of DSI as a strategic initiative for enhancing business outcomes. Additionally, the mediated pathway through AI offers further insights; the positive relationship between DSI and AI, with a coefficient of 0.4234, suggests that increased digital innovation leads to greater AI adoption. AI, in turn, positively influences BPer, with a coefficient of 0.5256, underscoring AI's role in enhancing the impact of DSI on BPer.

The analysis establishes that BPer has a consistently strong and positive effect on various BPer indicators, with standardized coefficients ranging from 1.1163 to 1.7965. This suggests that BPer plays a crucial role in driving business outcomes, significantly influencing all observed variables. The direct impact of DSI on BPer, with a standardized coefficient of 0.4585, reinforces the importance of digital innovation in improving BPer. Furthermore, the relationship between DSI and AI, with a standardized coefficient of 0.4727, indicates that DSI significantly influences AI adoption, which, although a secondary pathway, contributes to enhancing BPer. Overall, the findings highlight the interconnected roles of DSI and AI in shaping business success, with BPer serving as a key intermediary that translates these strategic initiatives into measurable performance improvements. Table 5 reviews the results of the estimation.

4.4 Confirmation of the mediating effect of AI on the relation between DSI and business performance on by-product data of customer feedback

The final analysis, conducted on a sample of 110 manufacturing firms primarily operating within a B2C context, reveals relevant insights between DSI, AI usage and BPer. The direct path from DSI to BPer is characterized by a coefficient of 0.5172, indicating a notable association where higher levels of DSI are linked with improved BPer. The standard error for

Table 4. Hypothesis H1 confirmatory results based on GSEM

Path	Coeff	Std. err	*z* value	*p* value	95% CI	Stdzed Coeff.
Direct effect						
DSI → BPer	1.060	0.1010	10.49	<0.000	0.8619 to 1.2582	0.6274
Indirect effect						
BPer → BP_V1	3.2530	0.0919	35.37	<0.000	3.0728 to 3.4332	1.2366
BPer → BP_V2	1.0306	0.0458	22.49	<0.000	0.9408 to 1.1204	1.3119
BPer → BP_V3	0.9679	0.0472	20.50	<0.000	0.8753 to 1.0604	1.1515
BPer → BP_V4	1.1138	0.0472	23.57	<0.000	1.0212 to 1.2065	1.5875
BPer → BP_V5	1.1239	0.0493	22.79	<0.000	1.0272 to 1.2206	1.6704

this coefficient is 0.1641, with a z-value of 3.15, and the relationship is statistically significant ($p = 0.002$). The 95% confidence interval ranges from 0.1957 to 0.8388, suggesting a reliable positive effect of DSI on BPer. The estimated variance for BPer is 0.2533, with a standard error of 0.0774, reflecting moderate variability in BPeroutcomes among the firms studied. These findings highlight the potential impact of DSI on BPer within the B2C manufacturing sector, underscoring the importance of adopting digital innovation strategies.

In addition to the direct effects, the mediated pathway through AI usage provides a further understanding of the influence of digital innovation on BPer. The path from DSI to AI exhibits a coefficient of 0.4094, with a standard error of 0.1042, indicating that higher levels of digital service innovation lead to increased AI utilization. This relationship is statistically significant ($z = 3.93$, $p < 0.0001$), with a confidence interval ranging from 0.2052 to 0.6136. However, the pathway from AI to BPer reveals a more nuanced relationship, with a coefficient of 0.1783 and a standard error of 0.1978, resulting in a z-value of 0.90 ($p = 0.367$). The confidence interval spans from −0.2094 to 0.5660, suggesting that while AI usage is positively associated with DSI, its direct effect on BPer may require further investigation. The variance components for the observed indicators of BPer (BP_V1 to BP_V5) range from 0.2591 to 0.3568, indicating varying degrees of association with BPer. These findings accentuate the roles of digital innovation and AI in shaping BPer, particularly through the utility of feedback data in understanding these dynamics.

The standardized coefficients provide a more nuanced understanding of the relationships between the variables in the model. The direct impact of DSI on BPer has a standardized coefficient of 0.5132, reinforcing the positive association between DSI and BPer. The relationship between DSI and AI is even stronger, with a standardized coefficient of 0.6238, indicating that DSI significantly influences AI adoption. However, the standardized coefficient for the path from AI to BPer is relatively low at 0.1161, suggesting that while AI contributes to BPer, its impact is more modest compared to DSI. The standardized coefficients for the paths from BPer to the BPer indicators (BP_V1 to BP_V5) vary, with values ranging from 0.8230 to 1.2354, highlighting the varying degrees of influence that BPer has on different aspects of BPer. Table 6 elucidates the data analysis conducted under GSEM method.

5. Discussion and conclusions

5.1 The DSI and business performance connection

The relationship between DSI and BPer is well-documented in existing literature, with studies highlighting its potential to enhance organizational outcomes (Kowalkowski *et al.*, 2023;

Path	Coeff	Std. err	z value	p value	95% CI	Stdzed Coeff
AI → BPer	0.5256	0.1443	3.64	<0.000	0.2427 to 0.8085	0.2622
DSI → BPer	0.8231	0.1416	5.81	<0.000	0.5456 to 1.1007	0.4585
DSI → AI	0.4234	0.0561	7.55	<0.000	0.3135 to 0.5333	0.4727

Table 5. Hypothesis H2 confirmatory results with by-product data of customer use, 244 firms

Path	Coeff	Std. err	z value	p value	95% CI	Stdzed Coeff
AI → BPer	0.1783	0.1978	0.90	0.037	−0.2094 to 0.5660	0.1161
DSI → BPer	0.5172	0.1641	3.15	0.002	0.1957 to 0.8388	0.5132
DSI → AI	0.4094	0.1042	3.93	<0.000	0.2052 to 0.6136	0.6238

Table 6. Hypothesis H2 confirmatory results with by-product data of customer feedback, 110 firms

Rabetino *et al.*, 2023). Prior research indicates that DSI can improve operational efficiencies, customer satisfaction and overall BPer (Opazo-Basáez *et al.*, 2024a, b; Sjödin *et al.*, 2020). The data from the current study align with these findings, supporting the theoretical framework (Kowalkowski *et al.*, 2023). Specifically, the direct path from DSI to BPer reveals a significant coefficient, indicating a positive correlation between higher levels of DSI and improved business outcomes. The GSEM results further suggest that DSI positively influences various dimensions of BPer. The path coefficients indicate that BPer indicators such as market share (BP_V1), market share growth rate (BP_V2), revenue growth (BP_V3), overall profitability (BP_V4) and return on sales (BP_V5) are positively associated with higher levels of DSI. The significant coefficients underscore the direct effect of DSI on these variables, confirming Hypothesis H1.

Competently, the direct effect of DSI on these variables is highlighted by the significant coefficients, indicating that DSI initiatives can contribute to notable improvements in these areas. However, while the positive impact of DSI on these performance metrics is consistent with existing literature, it is important to account for contextual factors that may influence these outcomes. For instance, the effectiveness of DSI may vary depending on the firm's industry, market conditions and technological infrastructure. Additionally, although DSI appears to enhance market share and revenue growth, its effect on profitability and return on sales may be moderated by the costs associated with implementing and sustaining digital innovations. Consequently, further analysis is needed to explore how different business contexts and strategies mediate or moderate the relationship between DSI and various performance metrics. The standardized coefficients suggest that the direct effect of DSI on BPer indicates that strategic initiatives focused on enhancing DSI could significantly improve overall BPer and related metrics. This relationship supports the hypothesis that DSI contributes to business success, as the impact of DSI on BPer confirms its role in influencing performance outcomes. By effectively leveraging DSI, organizations can achieve measurable improvements in performance metrics, thereby supporting the hypothesis that a strong DSI strategy can lead to better business results. Figure 2 describes the interconnection results.

5.2 Mediating effects of AI using by-product customer data of usage

In the mediation effect model, connected to hypothesis H2, relevant findings revealed that DSI directly impacts AI adoption within firms, facilitating a higher level of technological integration and innovation. Specifically, the path from DSI to AI demonstrates a strong

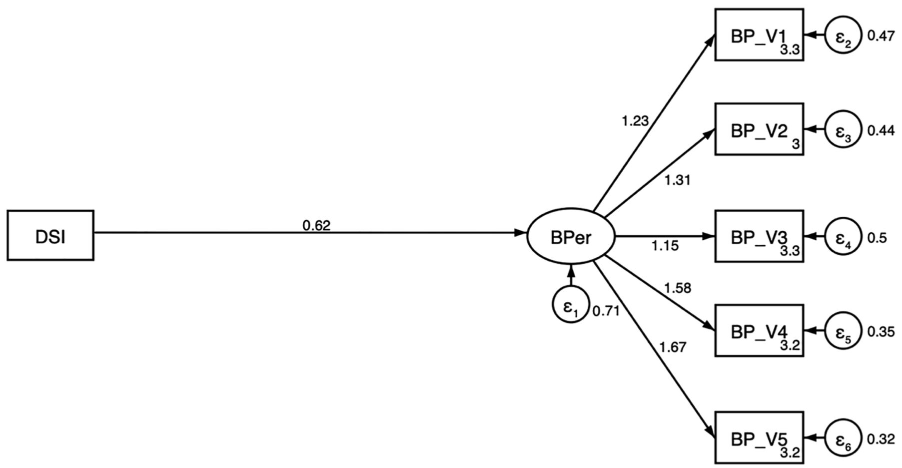

Figure 2.
GSEM of hypothesis H1 estimation and validation

influence, suggesting that firms investing in DSI will be more predisposed to adopt AI technologies. This embracing, in turn, enhances various aspects of BPer, including market share, market share growth rate, revenue growth, overall profitability and return on sales. However, the direct pathway from DSI to BPer remains pronounced, indicating that, while AI serves as a valuable intermediary, the foundational impact of DSI on BPer is robust. This aligns with the theoretical framework presented, which posits that digital innovations are crucial for contemporary business success (Abou-foul *et al.*, 2021; Favoretto *et al.*, 2022). Previous research, such as studies by Kowalkowski *et al.* (2023) and Rabetino *et al.* (2023), supports this notion, emphasizing the transformative potential of DSI in driving operational efficiencies and strategic growth.

The results highlight the nuanced role of AI when informed by by-product data from customer use. In B2B contexts, such data are instrumental in refining AI algorithms and enhancing decision-making processes. By-product data provides AI with rich, contextual insights that traditional data sources may overlook, thus enabling more accurate predictions and strategic recommendations (Huang and Rust, 2018; Payne *et al.*, 2021). This aligns with the OIPT, which emphasizes the importance of leveraging diverse data sources to improve decision-making capabilities (Haußmann *et al.*, 2012). However, it is crucial to note that while AI significantly enhances the impact of DSI on BPer, its effectiveness is contingent upon the quality and relevance of the data it processes (Bosse *et al.*, 2023; Qi *et al.*, 2023). The integration of high-quality by-product data ensures that AI can offer actionable insights, thereby reinforcing its role as a strategic tool in enhancing business outcomes (Opazo-Basáez *et al.*, 2023).

Overall, the analysis reveals distinct pathways through which DSI influences BPer. The direct impact of DSI on BPer is moderately strong, evidenced by a standardized coefficient of 0.4585, indicating that enhancements in DSI lead to measurable improvements in BPer. The mediated relationship involving AI also shows significant influence, with DSI positively affecting AI adoption (coefficient of 0.4727), and AI subsequently contributing BPer (coefficient of 0.2622). The standardized coefficients for the relationship between BPer and individual BPer indicators (BP V1 to BP V5) range from 1.1163 to 1.7965, with BP V5 and BP V4 demonstrating the strongest connections. These coefficients underline the critical role of BPer as a driver of business success, influenced both directly by DSI and indirectly through AI.

Conclusively, the data suggest that, while direct implementation of DSI provides immediate benefits to BPer, it introduces additional layers of complexity and potential for manufacturers. The effectiveness of AI as a mediator depends heavily on the quality and management of data within the firm, highlighting the need for robust data infrastructure. While the direct pathway from DSI to BPer remains important, the strategic deployment of AI can enhance these effects, provided that firms are equipped to manage and leverage data effectively. Therefore, the decision between pursuing a direct or mediated pathway should consider the organization's data capabilities, ensuring that AI acts as a complementary tool rather than a standalone driver of BPer. Figure 3 summarizes the evidence of the results and analysis.

5.3 Mediating effects of AI using by-product customer feedback data

The results of the Equation Model (GSEM) involving 110 manufacturing firms operating within a B2C context reveal noteworthy insights into the relationship between DSI, AI and BPer. The direct path from DSI to BPer is strong, indicating that firms implementing higher levels of DSI tend to exhibit improved BPer. When AI is introduced as a mediator, the relationship between DSI and BPer becomes more nuanced. The path from DSI to AI shows a positive relationship, suggesting that firms with substantial DSI investments are more likely

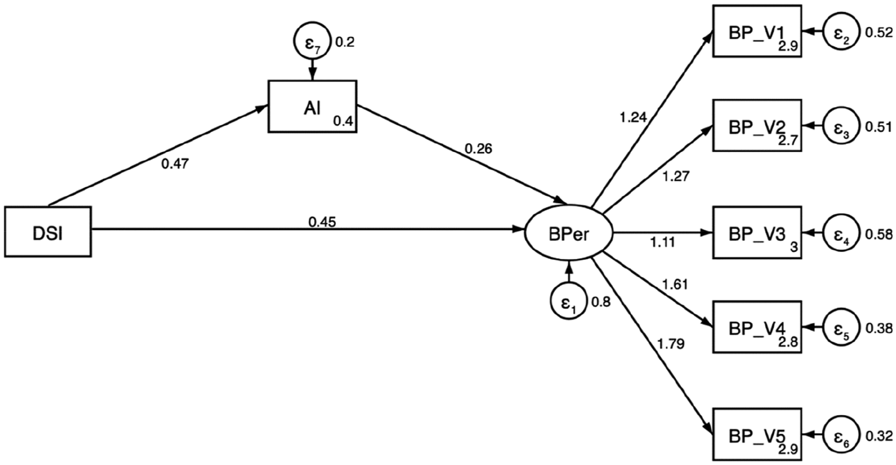

Figure 3.
GSEM of hypothesis H2 validated with by-product data base on USE (B2B)

to adopt AI technologies. This AI adoption, in turn, positively influences BPer, though the effect is less pronounced compared to the direct DSI–BPer link. This aligns with prior studies, such as those by Opazo-Basáez *et al.* (2022) and Burton *et al.* (2023), which highlight the critical role of digital innovations in driving business success, though the additional layer of AI introduces complexity in achieving these outcomes.

Therefore, the analysis reveals that in B2C contexts, customer feedback data provides valuable insights by enhancing AI algorithms, leading to better decision-making processes (Lee *et al.*, 2023). This aligns with the OIPT, emphasizing the importance of diverse data sources for effective decision-making (Haußmann *et al.*, 2012). An important limitation, however, is the effectiveness of AI as a mediator is contingent upon the quality and relevance of the feedback data. High-quality feedback data enable AI to offer actionable insights, reinforcing its role in improving BPer. The study suggests that while AI can enhance the impact of DSI on business outcomes, its effectiveness heavily relies on the proper management and utilization of customer feedback data.

Thus, the decision between pursuing a direct relationship between DSI and BPer versus a mediated approach involving AI hinges on the firm's ability to manage and leverage data effectively. Direct DSI implementation provides clear and immediate improvements in BPer. Nonetheless, when AI is incorporated, the potential for enhanced outcomes increases, provided that the AI is trained with comprehensive and relevant data. The study indicates that while AI adds value, the foundational impact of DSI remains robust. Firms must therefore consider their data infrastructure capabilities to maximize the benefits of AI-mediated strategies. The integration of AI, charged with high-quality customer feedback data, can amplify the benefits of DSI, though it requires substantial investment in data management practices. This nuanced understanding underscores the need for strategic alignment between DSI initiatives and AI deployment to achieve optimal BPer. Figure 4 summarizes the evidence base on the GSEM estimation.

6. Implications

The present study expands the research and comprehension of the relationship between DSI, AI and BPer within a service-based business model. By examining the strategic use of data-driven insights, particularly the application of by-product data from customer usage and

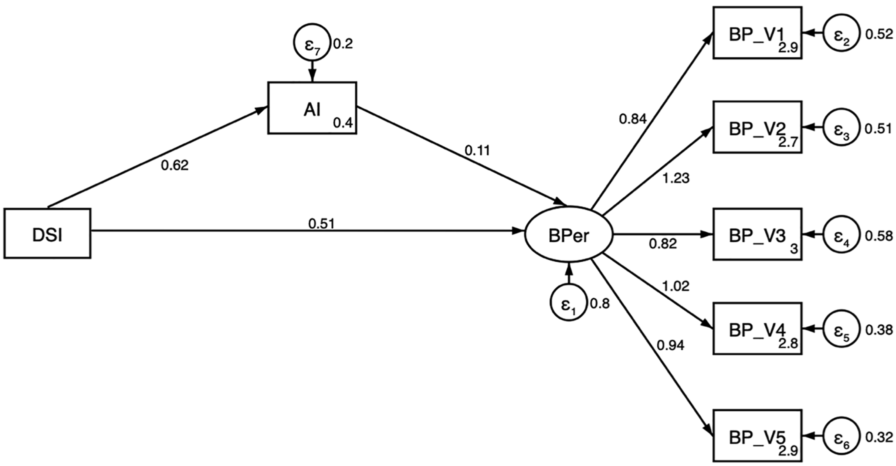

Figure 4.
GSEM of hypothesis H2 validated with by-product database on FEEDBACK (B2C)

feedback through AI, this research establishes a connection between these core components of a business strategy and outcomes. Subsequently, the conclusions presented will contribute to an understanding of how DSI and AI interact to influence BPer within the context of the digital economy. It will help to advance the field of DSI by illustrating that the relation with AI knowledge and ecosystems are not merely technological advancements but are also critical elements in driving growth and operational efficiency (Bustinza *et al.*, 2022; Vendrell-Herrero *et al.*, 2021a, b). Integration of B2B usage data and B2C feedback data into AI learning and decision-making processes enables technology to generate precise and impactful decisions (Kowalkowski *et al.*, 2023; Xie, 2023). Therefore, the study provides insights into how businesses can utilize AI technologies to secure a competitive advantage and foster sustainable growth within an increasingly dynamic digital landscape.

6.1 Theoretical implications

The findings of this research contribute to the understanding and development of DSI theory. By elucidating the relationship between DSI, AI and BPer, the study highlights the multifaceted nature of DSI, showing that it is not purely a technological approach but a comprehensive strategy that requires the integration of robust technologies. The results suggest that DSI impacts various BPer indicators such as market share, revenue growth and profitability, which can be further examined through the mediation of AI. This relationship indicates that for DSI to effectively influence BPer, it must be supported by advanced technologies like AI that can process and analyze complex data (Enholm *et al.*, 2022). Thus, DSI theory benefits from recognizing the need for such technological mediations, enabling a deeper and more precise impact on strategic business outcomes. This approach supports a broader measurement framework, connecting DSI with multiple performance indicators and demonstrating the intrinsic paths through which these indicators interact.

Furthermore, the integration of DSI with OIPT offers a nuanced perspective on the strategic value of DSI. OIPT suggests that organizations must efficiently process diverse and complex information to make informed decisions (Haußmann *et al.*, 2012; Rogers *et al.*, 1999). This study bridges DSI and OIPT by demonstrating how DSI, enhanced by AI, enables firms to process by-product data from customer use and feedback effectively. Such data provide rich contextual insights that traditional data sources may overlook, thus improving decision-making processes (Opazo-Basáez *et al.*, 2022). The research underscores the importance of acquiring strong contextual data, which enhances the capacity of AI to support DSI initiatives. This bridging of DSI and OIPT highlights the theoretical advancement wherein DSI, supported by robust data processing capabilities, can offer significant strategic benefits, making the case for its broader adoption and deeper integration into business strategies (Vendrell-Herrero *et al.*, 2022).

6.2 Managerial implications

The presented research analysis highlights relevant managerial implications, particularly concerning the strategic training of AI algorithms using contextual data, specifically by-product data. Managers can justify the need for strategic models based on DSI by recognizing the direct relationship between innovation and technology. DSI facilitates the acquisition of contextual data, which in turn enables the more efficient and extensive training of AI algorithms (Vendrell-Herrero *et al.*, 2021a, b), allowing businesses to make informed decisions within predictive and prescriptive analytics frameworks. By leveraging by-product data, firms can enhance the accuracy and relevance of AI-driven insights, supporting more effective decision-making processes. Consequently, the integration of DSI and AI within business strategies underscores the importance of adopting innovative approaches to data management and technology utilization, thus ensuring that decision-making processes are grounded in robust and comprehensive data analysis. Thus, the presented approach reinforces the strategic alignment between technological advancements and business objectives, highlighting the critical role of DSI in driving organizational efficiency and competitiveness.

6.3 Limitations and future research avenues

As a study, the research is not without limitations, which open avenues to expand the proposed theories. First, future studies could benefit from a larger pool of companies that extends beyond the current geographical regions, expanding to a more global perspective and revealing how DSI impacts BPer across different cultural and economic landscapes. Finally, a need to develop a valid measurement scale for DSI is required. This scale would enable an examination of how DSI enhances benefits or, conversely, may decrease effectiveness in certain contexts. A larger sample would allow for more robust and generalizable findings. However, achieving this requires a longitudinal study that tracks the degree of DSI implementation according to its maturity and outcomes over time. An approach in this direction will create a maturity scale for DSI, offering deeper insights into the impact of DSI on firms' performance and providing a temporal dimension to the understanding of DSI's effectiveness. These suggestions aim to refine the research on DSI and AI's role in service-based business models, further contributing to the body of knowledge in this rapidly evolving field.

References

Abou-foul, M., Ruiz-Alba, J.L. and Soares, A. (2021), "The impact of digitalization and servitization on the financial performance of a firm: an empirical analysis", *Production Planning and Control*, Vol. 32 No. 12, pp. 975-989, doi: 10.1080/09537287.2020.1780508.

Abou-Foul, M., Ruiz-Alba, J.L. and López-Tenorio, P.J. (2023), "The impact of artificial intelligence capabilities on servitization: the moderating role of absorptive capacity-A dynamic capabilities perspective", *Journal of Business Research*, Vol. 157, pp. 148-2963, doi: 10.1016/j.jbusres.2022.113609.

Acciarini, C., Cappa, F., Boccardelli, P. and Oriani, R. (2023), "How can organizations leverage big data to innovate their business models? A systematic literature review", *Technovation*, Vol. 123, 102713.

Armstrong, J.S. and Overton, T.S. (1977), "Estimating nonresponse bias in mail surveys", *Journal of Marketing Research*, Vol. 14 No. 3, pp. 396-402.

Bag, S., Gupta, S., Kumar, A. and Sivarajah, U. (2021), "An integrated artificial intelligence framework for knowledge creation and B2B marketing rational decision making for improving firm performance", *Industrial Marketing Management*, Vol. 92, pp. 178-189, doi: 10.1016/J.INDMARMAN.2020.12.001.

Benzidia, S., Makaoui, N. and Bentahar, O. (2021), "The impact of big data analytics and artificial intelligence on green supply chain process integration and hospital environmental performance", *Technological Forecasting and Social Change*, Vol. 165, 120557, doi: 10.1016/J.TECHFORE.2020.120557.

Biemans, W. and Griffin, A. (2018), "Innovation practices of B2B manufacturers and service providers: are they really different?", *Industrial Marketing Management*, Vol. 75, pp. 112-124, doi: 10.1016/j.indmarman.2018.04.008.

Bonamigo, A., Frech, C.G. and Lopes, A.C.C. (2022), "Value co-creation in the B2B context: a diagnosis of knowledge management based on multiple case studies", *Journal of Business and Industrial Marketing*, Vol. 37 No. 7, pp. 1449-1462.

Bosse, D., Thompson, S. and Ekman, P. (2023), "In consilium apparatus: artificial intelligence, stakeholder reciprocity, and firm performance", *Journal of Business Research*, Vol. 155, 113402, doi: 10.1016/j.jbusres.2022.113402.

Brocke, J.V., Zelt, S. and Schmiedel, T. (2016), "On the role of context in business process management", *International Journal of Information Management*, Vol. 36 No. 3, pp. 486-495, doi: 10.1016/J.IJINFOMGT.2015.10.002.

Burton, J., Story, V.M., Zolkiewski, J. and Nisha, N. (2023), "Digital service innovation challenges faced during servitization: a multi-level perspective", *Journal of Service Management*, Vol. 35 No. 2, pp. 202-226, doi: 10.1108/JOSM-12-2022-0398.

Bustinza, O.F., Vendrell-Herrero, F., Gomes, E., Lafuente, E., Opazo-Basaez, M., Rabetino, R. and Vaillant, Y. (2018), "Product-service innovation and performance: unveiling the complexities", *International Journal of Business Environment*, Vol. 10 No. 2, pp. 95-111, doi: 10.1504/IJBE.2018.095819.

Bustinza, O.F., Vendrell-Herrero, F. and Gomes, E. (2020), "Unpacking the effect of strategic ambidexterity on performance: a cross-country comparison of MMNEs developing product-service innovation", *International Business Review*, Vol. 29 No. 6, 101569, doi: 10.1016/j.ibusrev.2019.01.004.

Bustinza, O.F., Opazo-Basaez, M. and Tarba, S. (2022), "Exploring the interplay between Smart Manufacturing and KIBS firms in configuring product-service innovation performance", *Technovation*, Vol. 118, 102258, January 2020, doi: 10.1016/j.technovation.2021.102258.

Cao, G., Duan, Y., Edwards, J.S. and Dwivedi, Y.K. (2021), "Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making", *Technovation*, Vol. 106, 102312.

Carlos Monroy-Osorio, J., Opazo-Basáez, M. and Vendrell-Herrero, F. (2023), "Consumer goods: from mass consumption to servitization", in *Handbook of Industrial Development*, Edward Elgar Publishing, pp. 232-247, doi: 10.4337/9781800379091.00024.

Cenamor, J., Rönnberg Sjödin, D. and Parida, V. (2017), "Adopting a platform approach in servitization: leveraging the value of digitalization", *International Journal of Production Economics*, Vol. 192, pp. 54-65, November 2015, doi: 10.1016/j.ijpe.2016.12.033.

Dalenogare, L.S., Le Dain, M.A., Ayala, N.F., Pezzotta, G. and Frank, A.G. (2023), "Building digital servitization ecosystems: an analysis of inter-firm collaboration types and social exchange mechanisms among actors", *Technovation*, Vol. 124, 102756, doi: 10.1016/j.technovation.2023.102756.

Dawes, J. (2009), “The effect of service price increases on customer retention: the moderating role of customer tenure and relationship breadth”, *Journal of Service Research*, Vol. 11 No. 3, pp. 232-245, doi: 10.1177/1094670508328986.

de Haan, E., Verhoef, P.C. and Wiesel, T. (2015), “The predictive ability of different customer feedback metrics for retention”, *International Journal of Research in Marketing*, Vol. 32 No. 2, pp. 195-206, doi: 10.1016/j.ijresmar.2015.02.004.

DeCanio, S.J. and Watkins, W.E. (1998), “Information processing and organizational structure”, *Journal of Economic Behavior and Organization*, Vol. 36 No. 3, pp. 275-294, doi: 10.1016/S0167-2681(98)00096-1.

Demchenko, Y., Grosso, P., De Laat, C. and Membrey, P. (2013), “Addressing big data issues in scientific data infrastructure”, *2013 International Conference on Collaboration Technologies and Systems (CTS)*, IEEE, pp. 48-55.

Dubey, R., Gunasekaran, A., Childe, S.J., Bryde, D.J., Giannakis, M., Foropon, C., Roubaud, D. and Hazen, B.T. (2020), “Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: a study of manufacturing organisations”, *International Journal of Production Economics*, Vol. 226, 107599, doi: 10.1016/J.IJPE.2019.107599.

Egelhoff, W.G. (1991), “Information-processing theory and the multinational enterprise”, *Journal of International Business Studies*, Vol. 22 No. 3, pp. 341-368, doi: 10.1057/palgrave.jibs.8490306.

Enholm, I.M., Papagiannidis, E., Mikalef, P. and Krogstie, J. (2022), “Artificial intelligence and business value: a literature review”, *Information Systems Frontiers*, Vol. 24 No. 5, pp. 1709-1734, doi: 10.1007/S10796-021-10186-W/TABLES/8.

Eriksson, T. and Heikkilä, M. (2023), “Capabilities for data-driven innovation in B2B industrial companies”, *Industrial Marketing Management*, Vol. 111, pp. 158-172, doi: 10.1016/j.indmarman.2023.04.005.

Favoretto, C., Mendes, G.H.S., Oliveira, M.G., Cauchick-Miguel, P.A. and Coreynen, W. (2022), “From servitization to digital servitization: how digitalization transforms companies’ transition towards services”, *Industrial Marketing Management*, Vol. 102, pp. 104-121, doi: 10.1016/j.indmarman.2022.01.003.

Gallo, H., Khadem, A. and Alzubi, A. (2023), “The relationship between big data analytic-artificial intelligence and environmental performance: a moderated mediated model of green supply chain collaboration (GSCC) and top management commitment (TMC)”, *Discrete Dynamics in Nature and Society*, Vol. 2023 No. 1, 4980895.

Gebauer, H., Paiola, M., Saccani, N. and Rapaccini, M. (2021), “Digital servitization: crossing the perspectives of digitization and servitization”, *Industrial Marketing Management*, Vol. 93, pp. 382-388, doi: 10.1016/j.indmarman.2020.05.011.

Goh, S.H. and Eldridge, S. (2019), “Sales and operations planning: the effect of coordination mechanisms on supply chain performance”, *International Journal of Production Economics*, Vol. 214, pp. 80-94.

Haenlein, M. and Kaplan, A. (2019), “A brief history of artificial intelligence: on the past, present, and future of artificial intelligence”, *California Management Review*, Vol. 61 No. 4, pp. 5-14, doi: 10.1177/0008125619864925.

Häikiö, J. and Koivumäki, T. (2016), “Exploring digital service innovation process through value creation”, *Journal of Innovation Management*, Vol. 4 No. 2, pp. 96-124, doi: 10.24840/2183-0606_004.002_0006.

Hallowell, R. (1996), “The relationships of customer satisfaction, customer loyalty, and profitability: an empirical study”, *International Journal of Service Industry Management*, Vol. 7 No. 4, pp. 27-42, doi: 10.1108/09564239610129931.

Haußmann, C., Dwivedi, Y.K., Venkitachalam, K. and Williams, M.D. (2012), “A summary and review of Galbraith’s organizational information processing theory”, in Dwivedi, Y., Wade, M. and

Schneberger, S. (Eds), *Information Systems Theory, Integrated Series in Information Systems*, Springer, New York, NY, Vol. 29, doi: 10.1007/978-1-4419-9707-4_5.

Huang, M.H. and Rust, R.T. (2018), "Artificial intelligence in service", *Journal of Service Research*, Vol. 21 No. 2, pp. 155-172, doi: 10.1177/1094670517752459/ASSET/IMAGES/LARGE/10.1177_1094670517752459-FIG4.JPEG.

Hübner, D., Wagner, S.M. and Kurpjuweit, S. (2018), "The service recovery paradox in B2B relationships", *Journal of Business and Industrial Marketing*, Vol. 33 No. 3, pp. 291-302, doi: 10.1108/JBIM-03-2016-0055.

Jajja, M.S.S., Kannan, V.R., Brah, S.A. and Hassan, S.Z. (2017), "Linkages between firm innovation strategy, suppliers, product innovation, and business performance", *International Journal of Operations and Production Management*, Vol. 37 No. 8, pp. 1054-1075, doi: 10.1108/IJOPM-09-2014-0424.

Jovanovic, M., Sjödin, D. and Parida, V. (2021), "Co-evolution of platform architecture, platform services, and platform governance: expanding the platform value of industrial digital platforms", *Technovation*, Vol. 118, 102218, January, doi: 10.1016/j.technovation.2020.102218.

Kamp, B., Zabala, K. and Zubiaurre, A. (2023), "How can machine tool builders capture value from smart services? Avoiding the service and digitalization paradox", *Journal of Business and Industrial Marketing*, Vol. 38 No. 2, pp. 303-316, doi: 10.1108/JBIM-12-2021-0588.

Karwatzki, S., Dytynko, O., Trenz, M. and Veit, D. (2017), "Beyond the personalization–privacy paradox: privacy valuation, transparency features, and service personalization", *Journal of Management Information Systems*, Vol. 34 No. 2, pp. 369-400, doi: 10.1080/07421222.2017.1334467.

Kohtamäki, M., Parida, V., Oghazi, P., Gebauer, H. and Baines, T. (2019), "Digital servitization business models in ecosystems: a theory of the firm", *Journal of Business Research*, Vol. 104 June, pp. 380-392, doi: 10.1016/j.jbusres.2019.06.027.

Kohtamäki, M., Parida, V., Patel, P.C. and Gebauer, H. (2020), "The relationship between digitalization and servitization: the role of servitization in capturing the financial potential of digitalization", *Technological Forecasting and Social Change*, Vol. 151, 119804.

Kohtamäki, M., Rabetino, R., Parida, V., Sjödin, D. and Henneberg, S. (2022), "Managing digital servitization toward smart solutions: framing the connections between technologies, business models, and ecosystems", *Industrial Marketing Management*, Vol. 105, pp. 253-267, doi: 10.1016/J.INDMARMAN.2022.06.010.

Kowalczyk, M. and Buxmann, P. (2014a), "Big data and information processing in organizational decision processes", *Business and Information Systems Engineering*, Vol. 6 No. 5, pp. 267-278, doi: 10.1007/s12599-014-0341-5.

Kowalczyk, M. and Buxmann, P. (2014b), "Big data and information processing in organizational decision processes: a multiple case study", *Business and Information Systems Engineering*, Vol. 6 No. 5, pp. 267-278, doi: 10.1007/S12599-014-0341-5/FIGURES/6.

Kowalkowski, C., Wirtz, J. and Ehret, M. (2023), "Digital service innovation in B2B markets", *Journal of Service Management*, Vol. 35 No. 2, pp. 280-305, doi: 10.1108/JOSM-12-2022-0403.

Lee, P.S., Chakraborty, I. and Banerjee, S. (2023), "Artificial intelligence applications to customer feedback research: a review", in Sudhir, K. and Toubia, O. (Eds), *Artificial Intelligence in Marketing*, Emerald Publishing, Vol. 20, pp. 169-190, doi: 10.1108/S1548-643520230000020010.

Lehner, O.M., Ittonen, K., Silvola, H., Ström, E. and Wührleitner, A. (2022), "Artificial intelligence based decision-making in accounting and auditing: ethical challenges and normative thinking", *Accounting, Auditing & Accountability Journal*, Vol. 35 No. 9, pp. 109-135, doi: 10.1108/AAAJ-09-2020-4934.

Lenka, S., Parida, V. and Wincent, J. (2016), "Digitalization capabilities as enablers of value co-creation in servitizing firms", *Psychology and Marketing*, Vol. 34 No. 1, pp. 92-100.

Loureiro, S.M.C., Guerreiro, J. and Tussyadiah, I. (2021), "Artificial intelligence in business: state of the art and future research agenda", *Journal of Business Research*, Vol. 129, pp. 911-926, doi: 10.1016/J.JBUSRES.2020.11.001.

Madanaguli, A., Sjödin, D., Parida, V. and Mikalef, P. (2024), "Artificial intelligence capabilities for circular business models: research synthesis and future agenda", *Technological Forecasting and Social Change*, Vol. 200, 123189, doi: 10.1016/J.TECHFORE.2023.123189.

Manser Payne, E.H., Dahl, A.J. and Peltier, J. (2021), "Digital servitization value co-creation framework for AI services: a research agenda for digital transformation in financial service ecosystems", *The Journal of Research in Indian Medicine*, Vol. 15 No. 2, pp. 200-222, doi: 10.1108/JRIM-12-2020-0252.

Marchena Sekli, G.F. and De La Vega, I. (2021), "Adoption of big data analytics and Its impact on organizational performance in higher education mediated by knowledge management", *Journal of Open Innovation: Technology, Market, and Complexity*, Vol. 7 No. 4, p. 221.

Marcon, É., Marcon, A., Ayala, N.F., Frank, A.G., Story, V., Burton, J., Raddats, C. and Zolkiewski, J. (2022), "Capabilities supporting digital servitization: a multi-actor perspective", *Industrial Marketing Management*, Vol. 103, pp. 97-116, doi: 10.1016/j.indmarman.2022.03.003.

Marić, J., Pejić Bach, M. and Gupta, S. (2024), "The origins of digital service innovation (DSI): systematic review of ontology and future research agenda", *Journal of Service Management*, Vol. 35 No. 2, pp. 141-175, doi: 10.1108/JOSM-12-2022-0404.

Martín-Peña, M.L., Sánchez-López, J.M. and Díaz-Garrido, E. (2019), "Servitization and digitalization in manufacturing: the influence on firm performance", *Journal of Business and Industrial Marketing*, Vol. 35 No. 3, pp. 564-574, doi: 10.1108/JBIM-12-2018-0400.

Mikalef, P. and Gupta, M. (2021), "Artificial intelligence capability: conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance", *Information and Management*, Vol. 58 No. 3, 103434, doi: 10.1016/J.IM.2021.103434.

Miller, K.D., Gomes, E. and Lehman, D.W. (2019), "Strategy restoration", *Long Range Planning*, Vol. 52 No. 5, 101855, doi: 10.1016/j.lrp.2018.10.005.

Narvaiza, L., Campos, J.A., Martín-Peña, M.L. and Díaz-Garrido, E. (2023), "Characterizing digital service innovation: phases, actors, functions and interactions in the context of a digital service platform", *Journal of Service Management*, Vol. 35 No. 2, pp. 253-279, doi: 10.1108/JOSM-12-2022-0401.

Opazo Basáez, M., Vendrell-Herrero, F., Bustinza, O.F. and Raddats, C. (2024), "Guest editorial: digital service innovation: ontology, context and theory", *Journal of Service Management*, Vol. 35 No. 2, pp. 129-140, doi: 10.1108/JOSM-03-2024-498.

Opazo-Basáez, M., Vendrell-Herrero, F. and Bustinza, O.F. (2022), "Digital service innovation: a paradigm shift in technological innovation", *Journal of Service Management*, Vol. 33 No. 1, pp. 97-120, doi: 10.1108/JOSM-11-2020-0427.

Opazo-Basáez, M., Vendrell-Herrero, F., Bustinza, O.F., Vaillant, Y. and Marić, J. (2023), "Is digital transformation equally attractive to all manufacturers? Contextualizing the operational and customer benefits of smart manufacturing", *International Journal of Physical Distribution and Logistics Management*, Vol. 53 No. 4, pp. 489-511, doi: 10.1108/ijpdlm-12-2021-0538.

Opazo-Basáez, M., Monroy-Osorio, J.C. and Marić, J. (2024a), "Evaluating the effect of green technological innovations on organizational and environmental performance: a treble innovation approach", *Technovation*, Vol. 129, 102885, doi: 10.1016/j.technovation.2023.102885.

Opazo-Basáez, M., Bustinza, O.F. and Molina, L.M. (2024b), "The effect of industrial solution services (ISS) on innovation performance: the moderating role of sustainable development goals (SDGs)", *Journal of Cleaner Production*, Vol. 455, 142265, doi: 10.1016/j.jclepro.2024.142265.

Opresnik, D. and Taisch, M. (2015), "The value of Big Data in servitization", *International Journal of Production Economics*, Vol. 165, pp. 174-184, doi: 10.1016/j.ijpe.2014.12.036.

Paiola, M., Schiavone, F., Grandinetti, R. and Chen, J. (2021), "Digital servitization and sustainability through networking: some evidences from IoT-based business models", *Journal of Business Research*, Vol. 132, pp. 507-516, doi: 10.1016/J.JBUSRES.2021.04.047.

Palmer, T.M. and Sterne, J.A.C. (2015), "Fitting fixed- and random-effects meta-analysis models using structural equation modeling with the sem and gsem commands", *STATA Journal: Promoting Communications on Statistics and Stata*, Vol. 15 No. 3, pp. 645-671, doi: 10.1177/1536867X1501500303.

Park, E., Jang, Y., Kim, J., Jeong, N.J., Bae, K. and del Pobil, A.P. (2019), "Determinants of customer satisfaction with airline services: an analysis of customer feedback big data", *Journal of Retailing and Consumer Services*, Vol. 51, pp. 186-190, doi: 10.1016/j.jretconser.2019.06.009.

Paschen, J., Kietzmann, J. and Kietzmann, T.C. (2019), "Artificial intelligence (AI) and its implications for market knowledge in B2B marketing", *Journal of Business and Industrial Marketing*, Vol. 34 No. 7, pp. 1410-1419, doi: 10.1108/JBIM-10-2018-0295.

Payne, E.H.M., Peltier, J. and Barger, V.A. (2021), "Enhancing the value co-creation process: artificial intelligence and mobile banking service platforms", *The Journal of Research in Indian Medicine*, Vol. 15 No. 1, pp. 68-85, doi: 10.1108/JRIM-10-2020-0214.

Peltier, J.W., Dahl, A.J. and Schibrowsky, J.A. (2023), "Artificial intelligence in interactive marketing: a conceptual framework and research agenda", *The Journal of Research in Indian Medicine*, Vol. 18 No. 1, pp. 54-90, doi: 10.1108/JRIM-01-2023-0030.

Porter, M.E. and Heppelmann, J.E. (2016), "How smart, connected products are transforming companies", *Harvard Business Review*, Vol. 94 Nos 1-2, pp. 24-24.

Qi, B., Shen, Y. and Xu, T. (2023), "An artificial-intelligence-enabled sustainable supply chain model for B2C E-commerce business in the international trade", *Technological Forecasting and Social Change*, Vol. 191, 122491, doi: 10.1016/J.TECHFORE.2023.122491.

Qiu, A., Yu, Y. and Mccollough, J. (2023), "Can digital service trade promote the high-quality development of global manufacturing?-existence and mechanism", *Politics and Development*, Vol. 7 No. 3, pp. 191-213, doi: 10.1108/ITPD-06-2023-0014.

Quarteroni, S., Brambilla, M., Ceri, S. and Di Milano, P. (2013), "A bottom-up, knowledge-aware approach to integrating and querying web data services", *ACM Transactions on the Web*, Vol. 7 No. 4, pp. 1-33, doi: 10.1145/2493536.

Rabetino, R., Kohtamäki, M. and Huikkola, T. (2023), "Digital service innovation (DSI): a multidisciplinary (re)view of its origins and progress using bibliometric and text mining methods", *Journal of Service Management*, Vol. 35 No. 2, pp. 1757-5818, doi: 10.1108/JOSM-12-2022-0375.

Raddats, C. and Easingwood, C. (2010), "Services growth options for B2B product-centric businesses", *Industrial Marketing Management*, Vol. 39 No. 8, pp. 1334-1345, doi: 10.1016/j.indmarman.2010.03.002.

Raddats, C., Naik, P. and Ziaee Bigdeli, A. (2022), "Creating value in servitization through digital service innovations", *Industrial Marketing Management*, Vol. 104, pp. 1-13, doi: 10.1016/J.INDMARMAN.2022.04.002.

Ranjan, J. and Foropon, C. (2021), "Big data analytics in building the competitive intelligence of organizations", *International Journal of Information Management*, Vol. 56, 102231, doi: 10.1016/J.IJINFOMGT.2020.102231.

Ritala, P., Golnam, A. and Wegmann, A. (2014), "Coopetition-based business models: the case of Amazon.com", *Industrial Marketing Management*, Vol. 43 No. 2, pp. 236-249, doi: 10.1016/j.indmarman.2013.11.005.

Rogers, P.R., Miller, A. and Judge, W.Q. (1999), "Using information-processing theory to understand planning/performance relationships in the context of strategy", *Strategic Management Journal*, Vol. 20 No. 6, pp. 567-577, doi: 10.1002/(SICI)1097-0266(199906)20:6<567::AID-SMJ36>3.0.CO;2-K.

Shankar, V. (2018), "How artificial intelligence (AI) is reshaping retailing", *Journal of Retailing*, Vol. 94 No. 4, pp. vi-xi, doi: 10.1016/S0022-4359(18)30076-9.

Sheng, J., Amankwah-Amoah, J. and Wang, X. (2017), "A multidisciplinary perspective of big data in management research", *International Journal of Production Economics*, Vol. 191, pp. 97-112, doi: 10.1016/j.ijpe.2017.06.006.

Sjödin, D., Parida, V., Kohtamäki, M. and Wincent, J. (2020), "An agile co-creation process for digital servitization: a micro-service innovation approach", *Journal of Business Research*, Vol. 112, pp. 478-491, doi: 10.1016/j.jbusres.2020.01.009.

Sjödin, D., Parida, V., Palmié, M. and Wincent, J. (2021), "How AI capabilities enable business model innovation: scaling AI through co-evolutionary processes and feedback loops", *Journal of Business Research*, Vol. 134, pp. 574-587, doi: 10.1016/j.jbusres.2021.05.009.

Sjödin, D., Parida, V. and Kohtamäki, M. (2023), "Artificial intelligence enabling circular business model innovation in digital servitization: conceptualizing dynamic capabilities, AI capacities, business models and effects", *Technological Forecasting and Social Change*, Vol. 197, 122903, doi: 10.1016/j.techfore.2023.122903.

Song, P., Zheng, C., Zhang, C. and Yu, X. (2018), "Data analytics and firm performance: an empirical study in an online B2C platform", *Information and Management*, Vol. 55 No. 5, pp. 633-642, doi: 10.1016/J.IM.2018.01.004.

Soni, R., Baghel, A., Paliya, S., Mamtani, R. and Gupta, L. (2023), "Connection of big data analytics and artificial intelligence", *2023 IEEE International Students' Conference on Electrical, Electronics and Computer Science, SCEECS 2023*, Vol. 12, pp. 1-6, doi: 10.1109/SCEECS57921.2023.10063008.

Sorescu, A. (2017), "Data-driven business model innovation", *Journal of Product Innovation Management*, Vol. 34 No. 5, pp. 691-696, doi: 10.1111/JPIM.12398.

Soto Setzke, D., Riasanow, T., Böhm, M. and Krcmar, H. (2023), "Pathways to digital service innovation: the role of digital transformation strategies in established organizations", *Information Systems Frontiers*, Vol. 25 No. 3, pp. 1017-1037, doi: 10.1007/s10796-021-10112-0.

Sun, B., Li, S. and Zhou, C. (2006), "'Adaptive' learning and 'proactive' customer relationship management", *Journal of Interactive Marketing*, Vol. 20 Nos 3-4, pp. 82-96, doi: 10.1002/dir.20069.

Sun, S., Cegielski, C.G., Jia, L. and Hall, D.J. (2018), "Understanding the factors affecting the organizational adoption of big data", *Journal of Computer Information Systems*, Vol. 58 No. 3, pp. 193-203, doi: 10.1080/08874417.2016.1222891.

Sun, S., Hall, D.J. and Cegielski, C.G. (2020), "Organizational intention to adopt big data in the B2B context: an integrated view", *Industrial Marketing Management*, Vol. 86, pp. 109-121, doi: 10.1016/J.INDMARMAN.2019.09.003.

Vargo, S.L., Fehrer, J.A., Wieland, H. and Nariswari, A. (2023), "The nature and fundamental elements of digital service innovation", *Journal of Service Management*, Vol. 35 No. 2, pp. 227-252, doi: 10.1108/JOSM-02-2023-0052.

Vendrell-Herrero, F., Parry, G., Opazo-Basaez, M. and Sanchez-Montesinos, F.J. (2018), "Does business model experimentation in dynamic contexts enhance value capture?", *International Journal of Business Environment*, Vol. 10 No. 1, pp. 14-34, doi: 10.1504/IJBE.2018.093301.

Vendrell-Herrero, F., Bustinza, O.F. and Vaillant, Y. (2021a), "Adoption and optimal configuration of smart products: the role of firm internationalization and offer hybridization", *Industrial Marketing Management*, Vol. 95, pp. 41-53, doi: 10.1016/j.indmarman.2021.04.001.

Vendrell-Herrero, F., Bustinza, O.F. and Opazo-Basaez, M. (2021b), "Information technologies and product-service innovation: the moderating role of service R&D team structure", *Journal of Business Research*, Vol. 128, pp. 673-687, doi: 10.1016/j.jbusres.2020.01.047.

Vendrell-Herrero, F., Gomes, E., Opazo-Basaez, M. and Bustinza, O.F. (2022), "Knowledge acquisition throughout the lifecycle: product and industry learning frameworks", *Journal of Knowledge Management*, Vol. 26 No. 6, pp. 1633-1647, doi: 10.1108/JKM-05-2021-0387.

Vendrell-Herrero, F., Bustinza, O.F., Opazo-Basaez, M. and Gomes, E. (2023), "Treble innovation firms: antecedents, outcomes, and enhancing factors", *International Journal of Production Economics*, Vol. 255, 108682, doi: 10.1016/j.ijpe.2022.108682.

Verhoef, P.C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi Dong, J., Fabian, N. and Haenlein, M. (2021), "Digital transformation: a multidisciplinary reflection and research agenda", *Journal of Business Research*, Vol. 122, pp. 889-901, doi: 10.1016/J.JBUSRES.2019.09.022.

Vilkas, M., Bikfalvi, A., Rauleckas, R. and Marcinkevicius, G. (2022), "The interplay between product innovation and servitization: the mediating role of digitalization", *Journal of Business and Industrial Marketing*, Vol. 37 No. 11, pp. 2169-2184, doi: 10.1108/JBIM-03-2021-0182.

Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S.J.F., Dubey, R. and Childe, S.J. (2017), "Big data analytics and firm performance: effects of dynamic capabilities", *Journal of Business Research*, Vol. 70, pp. 356-365, doi: 10.1016/J.JBUSRES.2016.08.009.

Wamba-Taguimdje, S.-L., Fosso Wamba, S., Robert, J., Kamdjoug, K., Emmanuel, C. and Wanko, T. (2020), "Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects", *Business Process Management Journal*, Vol. 26 No. 7, pp. 1463-7154, doi: 10.1108/BPMJ-10-2019-0411.

Wasim, M., Ahmed, S., Kalsoom, T., Khan, M.S. and Rafi-Ul-Shan, P.M. (2024), "Market orientation and SME performance: moderating role of IoT and mediating role of creativity", *Journal of Small Business Management*, Vol. 62 No. 2, pp. 938-965, doi: 10.1080/00472778.2022.2100897.

Wirtz, J., Fritze, M.P., Jaakkola, E., Gelbrich, K. and Hartley, N. (2021), "Service products and productization", *Journal of Business Research*, Vol. 137, pp. 148-2963, doi: 10.1016/j.jbusres.2021.08.033.

Xie, T. (2023), "Artificial intelligence and automatic recognition application in B2C e-commerce platform consumer behavior recognition", *Soft Computing*, Vol. 27 No. 11, pp. 7627-7637, doi: 10.1007/S00500-023-08147-3/TABLES/6.

Xiong, Y., Xia, S. and Wang, X. (2020), "Artificial intelligence and business applications, an introduction", *International Journal of Technology Management*, Vol. 84 Nos 1-2, pp. 1-7, doi: 10.1504/IJTM.2020.112615.

Yuan, Y., Tan, H. and Liu, L. (2023), "The effects of digital transformation on supply chain resilience: a moderated and mediated model", *Journal of Enterprise Information Management*, Vol. 37 No. 2, pp. 488-510, doi: 10.1108/JEIM-09-2022-0333/FULL/PDF.

Zhou, D., Wu, Q., Lee, S., Li, X., Sun, K. and Peng, X. (2023), "Unpacking the mechanism linking digital servitization and manufacturing firm performance: the role of the service networks and slack resources", *Journal of Business and Industrial Marketing*, Vol. 39 No. 2, pp. 189-205, doi: 10.1108/JBIM-07-2022-0308.

Corresponding author
Juan Carlos Monroy-Osorio can be contacted at: jmonroyo@eafit.edu.co

CHAPTER 6. COMPENDIUM ARTICLE 3

Chapter 6, Compendium article 3

Charting the digital route to net-zero: A framework for sustainable industry practices

Reference: Monroy-Osorio, J. C. (2024). Charting the digital route to net-zero: A framework for sustainable industry practices. *Cleaner Logistics and Supply Chain*, 100191.

https://doi.org/10.1016/j.clscn.2024.100191

Abstract

This study investigates the application of a comprehensive framework for implementing digital strategies towards achieving net-zero emissions in Spanish manufacturing firms. It explores the adoption of digitally enabled and digital-first strategies in 354 medium-sized companies, utilizing Internet of Things (IoT) and Artificial Intelligence (AI) technologies to augment and reinvent environmental management practices. Digitally enabled strategies are found to be prevalent, optimizing existing processes through IoT for resource conservation and predictive maintenance. A modest yet growing number of firms adopt digital-first strategies, integrating AI to create innovative pathways for energy use optimization and waste reduction. However, a subset of firms remains reliant on traditional methods, indicating significant potential for digital integration. The paper highlights the strategic importance of digital tools in enhancing operational efficiencies and developing new, inherently sustainable business models. It emphasizes the need for an integrated approach that combines the strengths of digital innovation with traditional management to drive the industry towards a sustainable and net-zero future. The framework provides a nuanced classification of digital strategies and their contribution to net-zero objectives, offering insights into the effectiveness of these practices across various industrial sectors.

Cleaner Logistics and Supply Chain 13 (2024) 100191

Contents lists available at ScienceDirect

Cleaner Logistics and Supply Chain

journal homepage: www.journals.elsevier.com/cleaner-logistics-and-supply-chain

Charting the digital route to net-zero: A framework for sustainable industry practices

Juan Carlos Monroy-Osorio [a,b]

[a] School of Management, EAFIT University, Carrera 49 N° 7 Sur-50, Medellín, Colombia
[b] Deusto Business School, University of Deusto, Avda. de las Universidades, 24, Bilbao, Bizkaia, Spain

ARTICLE INFO

Keywords:
Net zero
Sustainability
digital strategies
Net zero strategies
Artificial intelligence
Internet of things

ABSTRACT

This study investigates the application of a comprehensive framework for implementing digital strategies towards achieving net-zero emissions in Spanish manufacturing firms. It explores the adoption of digitally enabled and digital-first strategies in 354 medium-sized companies, utilizing Internet of Things (IoT) and Artificial Intelligence (AI) technologies to augment and reinvent environmental management practices. Digitally enabled strategies are found to be prevalent, optimizing existing processes through IoT for resource conservation and predictive maintenance. A modest yet growing number of firms adopt digital-first strategies, integrating AI to create innovative pathways for energy use optimization and waste reduction. However, a subset of firms remains reliant on traditional methods, indicating significant potential for digital integration. The paper highlights the strategic importance of digital tools in enhancing operational efficiencies and developing new, inherently sustainable business models. It emphasizes the need for an integrated approach that combines the strengths of digital innovation with traditional management to drive the industry towards a sustainable and net-zero future. The framework provides a nuanced classification of digital strategies and their contribution to net-zero objectives, offering insights into the effectiveness of these practices across various industrial sectors.

1. Introduction

The global drive to achieve net-zero greenhouse gas emissions by mid-century presents an urgent challenge, requiring industries to adopt innovative and multidisciplinary approaches to manage atmospheric carbon levels effectively (Ganda, 2019; Tress et al., 2005). The concept of net-zero, often explained through the metaphor of a carbon bathtub, highlights the necessity of balancing emissions input and output to stabilize global temperatures (Cesar da Silva et al., 2021). Achieving this balance depends not only on reducing the influx of greenhouse gases into the atmosphere but also on developing advanced mechanisms for their removal and regeneration (Khan et al., 2020). Despite the emergence of various emission reduction technologies, significant gaps remain in understanding how digital innovations can support the widespread adoption of sustainable practices, particularly in industries with varying levels of digital infrastructure and capability (Vendrell-Herrero et al., 2021). This gap serves as a central focus of this study, which explores the role of digital tools in advancing sustainability efforts.

Digital technologies have emerged as indispensable tools in the quest to meet net-zero targets, offering transformative solutions that have the potential to revolutionize environmental monitoring, data analysis, and overall management practices (Kohtamäki et al., 2024). Key innovations, such as artificial intelligence (AI), advanced sensor technologies (IoT), and big data analytics, enhance both the precision and transparency of emissions tracking by enabling real-time monitoring of carbon outputs (Opazo-Basáez et al., 2018; Vendrell-Herrero et al., 2021). Through these advancements, companies are better equipped to coordinate their sustainability efforts with various stakeholders, improving the overall management of emissions across supply chains and aligning more effectively with environmental objectives. However, despite the transformative potential of these digital innovations, there remains limited clarity on how firms in different sectors are practically implementing these tools to align with broader net-zero goals. Existing research tends to emphasize the theoretical advantages of digital tools in improving operational efficiency and reducing emissions, but it often lacks a thorough exploration of the tangible benefits that companies experience when integrating these technologies into their daily operations (Falcke et al., 2024b; Jamwal et al., 2022). Moreover, the extent to which digital sustainability strategies can support long-term competitiveness and regulatory compliance is an area that remains underexplored, leaving a gap for further investigation.

E-mail address: jmonroyo@eafit.edu.co.

https://doi.org/10.1016/j.clscn.2024.100191
Received 26 April 2024; Received in revised form 25 September 2024; Accepted 9 November 2024

In this context, the Net-Zero framework proposed by Falcke et al. (2024a) introduces a structured approach to sustainability by categorizing strategies into two main pathways: digitally enabled and digital-first. The digitally enabled approach focuses on optimizing existing physical infrastructures by leveraging technologies, such as sensors, data analytics, and connected systems (Enholm et al., 2022). These technologies facilitate the creation of digital representations of physical processes, enabling more precise measurement, management, and ultimately, the reduction of emissions (Chirumalla, 2021). By contrast, the digital-first approach prioritizes the design and refinement of technology solutions from the beginning of the strategy and the firm, within the digital domain, before their implementation in the physical world (Kamble et al., 2022). This approach allows businesses to experiment with and scale sustainability practices in a cost-effective and emissions-reducing manner. Both strategies—digitally enabled and digital-first—are complementary, providing industries with flexible pathways to balance immediate decarbonization efforts with long-term regenerative goals (Falcke et al., 2024b). By employing these strategies, companies can work toward net-zero emissions while addressing the inherent challenges associated with legacy infrastructures and existing operational frameworks (Chehri et al., 2021).

However, the transition to digital sustainability strategies presents numerous significant challenges that require careful consideration (Abou-Foul et al., 2023). Over-reliance on technology can exacerbate existing inequalities in terms of resource access and infrastructure, particularly within industries or regions where digital adoption lags (Eriksson & Heikkilä, 2023). Furthermore, as companies increasingly rely on digital tools to manage their sustainability efforts, concerns surrounding data security and privacy become more pronounced (Buckley et al., 2020). The expanded use of data for emissions tracking and resource management introduces potential vulnerabilities that must be addressed through robust cybersecurity measures and comprehensive regulatory frameworks (Kohtamäki et al., 2020). Organizational and behavioral barriers also present substantial challenges (Brunetti et al., 2020). Many firms, especially those operating with deeply entrenched legacy systems or a culture resistant to change, may struggle to adopt new technologies quickly and efficiently (Cesar da Silva et al., 2021; Falcke et al., 2024a). These challenges underscore the need for a complete approach to sustainability, one that seamlessly integrates digital tools with traditional management practices while fostering a culture of innovation and adaptability within organizations.

While the benefits of digital technologies in advancing sustainability objectives are widely acknowledged, it is critical to address the organizational and behavioral barriers that may delay or hinder the adoption of these innovations (Foroudi et al., 2017). Resistance to change, especially within well-established industries, can impede the successful implementation of digital sustainability strategies, reducing their overall impact on emissions reduction and resource optimization (Verhoef et al., 2021). Furthermore, as companies transition toward digital-first models, there is a risk of exacerbating existing inequalities (Kurniawan et al., 2023). Smaller firms or those located in less developed regions may lack the financial and technological resources to invest in advanced digital infrastructure, putting them at a disadvantage compared to their larger or better-resourced counterparts (Opazo-Basáez et al., 2024a; Gebauer et al., 2021).

Integrating digital strategies with traditional management practices is essential for navigating the complexities associated with decarbonizing hard-to-abate sectors (Ganda, 2019). A holistic approach, which incorporates both digital innovations and conventional management techniques, ensures that efforts to achieve net-zero emissions address operational challenges and promote long-term sustainability goals (Vendrell-Herrero et al., 2021). By fostering a culture of innovation, adaptability, and sustainability, organizations can not only meet current regulatory requirements but also anticipate and influence future environmental standards (Shakeel et al., 2020). The combination of digital transformation and sustainability management offers a clear, actionable pathway to achieving net-zero emissions (Opazo-Basáez et al., 2018). This pathway provides strategic insights and directions for businesses, policymakers, and researchers alike (Lüdeke-Freund, 2020). Moreover, this integrated approach is crucial for ensuring that efforts to mitigate global warming are both effective and equitable, addressing a wide range of economic activities and societal needs (Buckley et al., 2020).

To address the gaps identified in the existing literature, this research aims to investigate the following key question: *How do companies that align with digital sustainability strategies perceive the benefits of a net-zero approach, predominantly through the use of digital strategies?*

By examining this question, the study seeks, not only to provide empirical evidence on the effectiveness of sustainable practices in firms, but also to contribute to a broader understanding of how digital strategies can drive sustainability focus to the industry. The research will classify and analyse the impact on Spanish companies within the digital sustainability framework developed by Falcke et al. (2024a), assessing how they implement and benefit from net-zero approaches. Ultimately, the study will contribute insights into the role of digital focus and strategies in fostering effective and equitable climate action, addressing both the immediate challenges of emissions reduction and the long-term sustainability objectives of businesses. The classification of 354 Spanish companies within Falcke et al.'s framework offers a comprehensive analysis by assessing how companies align their sustainability efforts with both digitally enabled and digital-first approaches. The research will provide key insights into the effectiveness of these strategies in driving progress toward net-zero emissions. This synthesis of perspectives offers an understanding of the multifaceted approaches needed to address climate change and highlights the importance of integrating digital innovations with traditional management practices in achieving net-zero goals.

2. Literature review

2.1. Pathways to net-zero through digitally enhanced environmental management

In the pursuit of net-zero emissions, the strategic integration of digital technologies plays a role in enhancing environmental management systems (Stern & Valero, 2021). Digital technologies, such as the Internet of Things (IoT), big data, artificial intelligence (AI), and blockchain, are vital for optimizing existing operational processes and enabling the transition to more sustainable and circular economic models (Kohtamäki et al., 2022). The integration of technologies provides a structured framework for leveraging data-driven insights and automation to achieve efficiency gains, reduce waste, and minimize emissions across industries (Rusch et al., 2023). Digital sustainability strategies, such as the Digitally Enabled Mitigation and Reduction approach, referred as strategies that leverage existing digital technologies to improve and optimize current operational systems in a way that reduces carbon emissions and increases sustainability (Kristoffersen et al., 2020). This concept focuses on enhancing the efficiency of established processes through the integration of digital technologies, such as IoT sensors, data analytics, and cloud computing, to refine and optimize traditional processes by including technology (Falcke et al., 2024a). For instance, IoT enable predictive maintenance in manufacturing settings, where equipment failures are foreseen before they occur, preventing downtime and ensuring operational continuity (Rusch et al., 2023). This proactive management of industrial systems not only optimizes resource use but also extends the life cycle of equipment, aligning with the broader goals of circular economy strategies (Shakeel et al., 2020).

Moreover, IoT technologies plays a role in supply chain optimization by embedding sensors in logistics and transportation networks. These sensors enable real-time monitoring of shipments, optimize delivery routes, and reduce fuel consumption, contributing to a reduced carbon footprint (Dubey et al., 2020). By enhancing the efficiency of supply chains, IoT helps companies streamline their operations and achieve more sustainable outcomes, allowing this technological strategy to be integrated with various other strategies, both digital and non-digital, that the company employs to support its approach to net-zero (Nižetić et al., 2020). Therefore, IoT acts as a key enabler for circular economy strategies by continuously optimizing processes and facilitating resource reuse. (Gebauer et al., 2021). However, beyond IoT, the concept of digital twins, for example, introduces another layer of innovation in the pursuit of net-zero emissions (Khan et al., 2020). Digital twins create virtual models of physical systems, enabling real-time monitoring, predictive analysis, and optimization of complex processes. These virtual representations allow companies to simulate different scenarios, identify inefficiencies, and implement solutions before making physical changes (Bag, 2023). For instance, a digital twin can simulate a factory's energy usage, predict energy peaks, and adjust energy flows to ensure efficient resource use (Falcke et al., 2024a). Such real-time adjustments can drastically reduce emissions and improve operational sustainability (Abou-Foul et al., 2023). Additionally, digital twins extend to the entire product life cycle, providing a comprehensive view of production, supply chains, and environmental impacts, which enhances the sustainability of processes across industries.

In this context, net-zero strategies approaches illustrate the incremental yet meaningful advancements that digital technologies offer in sustainable product management (Rusch et al., 2023). Although many of these innovations lead to incremental improvements, such as enhanced operational efficiency or better resource management, the potential for more radical changes in future scenarios is significant (Bag, 2023; Manish & Dave, 2023). Digital technologies not only support more efficient resource use but also enable the creation of new business models grounded in sustainability and circular economy principles (Huang & Rust, 2018). Consequently, in the other side of the digital ecosystem, digital-first removal and regeneration strategies can showcase the transformative potential of digital technologies. These strategies emphasize the design of inherently sustainable systems, leveraging digital simulations and prototypes (Opazo-Basáez et al., 2024a). Digital twins are particularly valuable in efforts related to ecosystem restoration and carbon capture, where sensors and data analytics monitor environmental conditions and optimize interventions to ensure maximal efficacy (Kurniawan et al., 2023).

The Digital-First approach, as outlined by Falcke et al. (2024a), focuses on building sustainability solutions from the ground up, using digital technologies as the foundation. Unlike the Digitally Enabled Mitigation and Reduction approach, which concentrates on optimizing existing systems, the Digital-First strategy embeds digital tools, such as artificial intelligence and digital twins, directly into the creation of new business processes. This allows companies to develop advanced carbon capture technologies, continuously monitoring and adjusting operations in real-time based on environmental feedback. Such an approach aligns with the goals of the circular economy, particularly in closing resource use loops by regenerating ecosystems and minimizing industrial carbon footprints (Kamble et al., 2022). The predictive capabilities of AI, combined with real-time data from IoT sensors, create a dynamic system that optimizes environmental interventions efficiently, ensuring sustainability goals are met in a constantly evolving manner (Rusch et al., 2023).

Therefore, digitally enhanced environmental strategies within the net-zero framework offer a pathway toward sustainability that aligns with the broader goals of the circular economy. These strategies, while often starting with incremental improvements, pave the way for radical innovations that redesign industrial processes and business models. As companies continue to integrate these digitally enabled solutions into various aspects of their operations, digital technologies will increasingly contribute to a resilient and sustainable future (Bailey et al., 2018). The use of real-time data, automation, and advanced digital tools will facilitate ongoing enhancements in environmental performance, bringing industries closer to their net-zero objectives (Rusch et al., 2023).

2.2. IoT as a digital enabled strategiy for net-zero

Achieving net-zero emissions requires the application of digitally enabled mitigation and reduction strategies, which integrate existing operational frameworks with digital advancements to optimize processes and enhance sustainability (Stern & Valero, 2021). These strategies focus on the use of technologies to refine current systems, leading to increased operational efficiency and environmental benefits, such as Internet of Things (IoT) (Paiola et al., 2021). For instance, integrating IoT sensors into factory settings can lead to significant energy savings by enabling real-time data collection and on-the-fly adjustments to energy consumption (Kurniawan et al., 2023; Sheng et al., 2017). This type of digital enhancement not only optimizes energy usage but also helps in reducing overall emissions, as noted by Falcke et al. (2024a). In addition, IoT enables proactive management of energy and resources through continuous monitoring. Sensors collect vast amounts of data that provide immediate feedback to adjust operations and conserve resources (Nižetić et al., 2020). The real-time visibility into operations that IoT provides allows for improvements in energy efficiency and sustainability across industries, such as manufacturing and logistics.

The implementation of IoT extends beyond energy management, playing a central role in supply chain optimization. By embedding sensors in transportation and logistics networks, companies can monitor routes, track shipments, and reduce fuel consumption by optimizing routes. This reduces the carbon footprint associated with transportation, demonstrating IoT's contribution to broader supply chain sustainability (Paiola et al., 2021). Additionally, in production settings, IoT sensors detect machinery wear and tear, enabling predictive maintenance, which reduces downtime and conserves resources by maintaining equipment before major breakdowns occur (Nižetić et al., 2020). Consequently, these digitally enabled strategies show how IoT can enhances the operational sustainability of existing infrastructures by promoting efficient resource use and minimizing emissions.

The concept of digitally enabled removal and regeneration strategies also benefits from IoT technology. In the context of carbon capture and ecosystem restoration, IoT systems enable precise monitoring and control over restoration projects. For example, sensors can monitor soil conditions and water levels in reforestation efforts, ensuring that resources are used efficiently, and restoration activities are aligned with environmental goals (Chehri et al., 2021). These IoT-driven systems can also support smart grid technology, integrating renewable energy sources and optimizing energy flows to minimize carbon emissions (Nižetić et al., 2020). By leveraging real-time data, these systems can adjust energy distribution, ensuring that energy is consumed efficiently and sustainably. Moreover, IoT's predictive capabilities extend to environmental monitoring (Benzidia et al., 2021). IoT sensors deployed in natural environments, such as forests and wetlands, provide continuous data on air quality, soil conditions, and weather patterns. These insights enable timely interventions to protect ecosystems from damage, and support reforestation efforts through IoT-driven drone technology, which can distribute seeds with precision (Falcke et al., 2024a). This combination of real-time monitoring and data-driven intervention exemplifies the role of digitally enabled technologies in environmental regeneration, as they offer scientifically informed, efficient approaches to large-scale restoration projects (Nižetić et al., 2020).

Thus, digitally enabled IoT solutions not only improve efficiency within established processes but also facilitate the development of new strategies for environmental preservation and restoration. These solutions, whether applied to energy management, supply chain optimization, or ecosystem restoration, demonstrate the potential of IoT to contribute to achieving net-zero emissions. The versatility and scalability of IoT technologies allow firms to implement sustainability practices tailored to their specific operational needs, making IoT a key component of digitally enabled net-zero strategies. Therefore, IoT technology plays a crucial role in digitally enabled strategies by enhancing both process optimization and sustainability outcomes. These technologies are not only transformative in their capacity to improve operational efficiency but also offer a pathway toward achieving broader sustainability goals through the intelligent management of resources and ecosystems (Paiola et al., 2021).

2.3. Artificial intelligence as a digital-first strategy for net-zero

In the context of net-zero strategies, Artificial Intelligence (AI) holds a significant role within digital-first approaches. This strategy focuses on embedding sustainability into business models and processes from the outset, with AI acting as a key tool for emissions reduction and environmental management (Falcke et al., 2024a; Haenlein & Kaplan, 2019). Unlike approaches that optimise existing infrastructures, digital-first frameworks develop systems that are designed to be sustainable from their inception, with digital technologies playing a central role. AI's capacity for data analysis and predictive analytics enables companies to integrate sustainability into their core strategies more effectively (Kurniawan et al., 2023).

Furthermore, a key aspect of digital-first strategies is the development of new processes facilitated by AI, rather than simply improving current practices. AI's ability to process large datasets and simulate complex scenarios allows businesses to design systems that prioritise sustainability (Shakeel et al., 2020). For example, AI can be used to simulate and optimise carbon capture technologies, ensuring these systems are efficient from the initial stages of development (Sjödin et al., 2023). This contrasts with retrofitting sustainability measures to existing processes, highlighting the proactive nature of the digital-first approach. In addition, AI plays a crucial role in environmental monitoring and ecosystem management, supporting real-time data collection and enabling timely interventions (Wamba-Taguimdje et al., 2020). This capacity for continuous monitoring allows businesses to manage resources more effectively and minimise environmental impact (Haenlein & Kaplan, 2019). AI's role in digital-first removal strategies is particularly relevant for activities such as carbon sequestration and ecosystem restoration, where its predictive and real-time capabilities can guide environmental management decisions (Khan et al., 2021).

AI's predictive functions are also important in supporting long-term sustainability goals (Manser Payne et al., 2021). By forecasting potential environmental challenges, AI helps companies implement preventive measures to avoid resource depletion and environmental degradation (Rabetino et al., 2023). This predictive capability is remarkably convenient in supply chain management, where AI can help businesses optimise their operations while staying aligned with sustainability targets (Opazo-Basáez et al., 2024b). This approach enables businesses to move beyond incremental efficiency improvements, allowing them to build processes that are fundamentally designed to meet sustainability objectives (Xiong et al., 2020). Similarly, the use of AI in digital-first strategies reflects a broader trend in business approaches to sustainability. As companies increasingly adopt technology-driven solutions, AI's role in resource management and operational optimisation becomes increasingly important (Kohtamäki et al., 2024). AI not only enhances existing sustainability efforts but also shapes the direction of future strategies, making it a key enabler in achieving net-zero objectives (Kamble et al., 2022).

By comparison, while the Digitally Enabled Mitigation and Reduction approach focuses on enhancing current systems, the Digital-First strategy uses AI to create new solutions that aim to achieve sustainability from the outset (Kurniawan et al., 2023). AI supports the circular economy's objectives by facilitating resource efficiency and reducing waste, which contributes to environmental sustainability (Rusch et al., 2023). In addition to its applications in environmental management, AI is increasingly being used to design new business models that are inherently sustainable (Manser Payne et al., 2021; Marcon et al., 2019). By leveraging AI for digital simulations and prototypes, companies can test and refine processes in virtual environments before implementing them in the physical world (Marcon et al., 2019). This reduces the risk of failure and ensures that new systems are optimized for sustainability from the start. For instance, digital twins—virtual models of physical systems—allow companies to monitor and manage the lifecycle of products and infrastructure, ensuring that resources are used efficiently, and waste is minimized (Kamble et al., 2022; Errandonea et al., 2020). These innovations reflect the potential of AI in shaping sustainability strategies.

Ultimately, the digital-first approach, with AI as a central component, offers significant advantages for industries seeking to meet net-zero objectives. AI's ability to optimize processes, predict inefficiencies, and create new solutions makes it an indispensable model of strategy for advancing environmental sustainability and also to represent a digitally first approach strategy focus (Opazo-Basáez et al., 2023). As companies continue to adopt AI-driven strategies, they will not only improve their operational efficiency but also contribute to broader sustainability efforts by integrating digital technologies into the very foundation of their business models (Qi et al., 2023). The strategic use of AI in this context ensures that companies are well-equipped to navigate the challenges of climate change and move closer to achieving their net-zero goals.

2.4. Framework strategy to categorize the contribution to a net-zero objective

Addressing the broader challenges of achieving net-zero emissions requires innovative approaches, and digital technologies such as IoT and AI offer promising solutions (Chirumalla, 2021; Falcke et al., 2024). Insights from recent studies on sustainability reporting, institutional logics, and collaborative innovation suggest that adopting a digital sustainability lens can complement traditional sustainability approaches (Kristoffersen et al., 2020; Lüdeke-Freund, 2020). Digital strategies for sustainability can be conceptualized within two key categories: digitally enabled, which focuses on enhancing the efficiency of existing physical assets through digital tools, and digital-first, which reimagines processes entirely from a digital perspective (Falcke et al., 2024a). This bifurcation illustrates the versatility of digital technologies in advancing environmental sustainability and demonstrates their strategic potential for companies seeking to contribute meaningfully to net-zero objectives (Sun et al., 2021). Therefore, while both IoT and AI technologies offer substantial benefits for improving environmental performance, they operate on different levels (Huikkola et al., 2020; Sheng et al., 2017; Shashi et al., 2019). IoT technologies provide incremental gains by optimizing current systems, whereas AI enables a more forward-looking approach that allows firms to strategize based on predictive insights and adaptive learning (Parida & Wincent, 2019). This distinction underscores the importance of both technologies in contributing to the broader goal of achieving net-zero emissions, though their respective impacts may vary depending on the specific needs and operational frameworks of individual firms (Kamp et al., 2023).

In addition, this transition toward a net-zero economy compels a comprehensive approach that encompasses both carbon removal and regeneration efforts (Piscicelli, 2023). This holistic perspective is essential, given the need to focus on strategies that yield a net-negative impact on emissions (Stern & Valero, 2021). Central to this approach is the application of quality criteria, such as additionality, permanence, and verification, which ensure that carbon removal initiatives result in tangible, measurable environmental benefits (Zameer et al., 2021). Previous research has largely concentrated on carbon accounting and pricing mechanisms, yet a clearer distinction between avoidance and removal credits is now required (Buckley et al., 2020; Cesar da Silva et al., 2021). Furthermore, the establishment of robust markets for high-quality carbon removal credits depends on stringent quality control and verification processes (Kurniawan et al., 2023). Considering these complexities, two hypotheses are posited to explore the relationship between technology adoption and environmental performance:

H1: There is a positive relationship between the implementation of IoT technologies and improved environmental performance.
H2: The adoption of AI-driven strategies significantly enhances environmental performance.

The first hypothesis is based on the potential of Internet of Things (IoT) technologies to enhance operational efficiency by providing real-time data and actionable insights. By integrating IoT systems, organizations can precisely monitor resource use, identify inefficiencies, and implement preventive maintenance. These capabilities are expected to improve environmental performance metrics, such as reducing energy consumption and emissions. The continuous data stream from IoT sensors enables companies to optimize operations, promoting sustainable practices over time (Hund et al., 2021). This hypothesis seeks to evaluate how IoT adoption drives measurable improvements in environmental performance, particularly in reducing emissions and conserving resources through real-time monitoring and predictive maintenance. Second hypothesis asserts that AI-driven strategies enhance environmental performance by offering innovative solutions for resource optimization, energy management, and carbon sequestration, beyond the incremental gains of traditional methods. AI technologies, particularly predictive analytics and machine learning, enable firms to analyze complex datasets, forecast trends, and optimize supply chains (Raddats & Easingwood, 2010). Contrasting IoT, which focuses on improving existing processes, AI drives a transformative shift by supporting proactive, data-driven decision-making. This hypothesis suggests that firms using AI will achieve greater environmental performance improvements compared to those relying on process enhancements through IoT. The predictive capabilities of AI help organizations anticipate and address environmental challenges, making these technologies essential for advancing sustainability goals.

Ultimately, while both IoT and AI technologies offer substantial benefits for improving environmental performance, they operate on different levels. IoT technologies provide incremental gains by optimizing current systems, whereas AI enables a more forward-looking approach that allows firms to strategize based on predictive insights and adaptive learning (Jamwal et al., 2022). This distinction underscores the importance of both technologies in contributing to the broader goal of achieving net-zero emissions, though their respective impacts may vary depending on the specific needs and operational frameworks of individual firms. The hypotheses presented here aim to clarify the relationship between these digital innovations and their role in enhancing environmental performance across various sectors. Table 1, adapted from Falcke et al. (2024a), presents a comprehensive framework that categorizes digital sustainability strategies into two primary approaches: augmenting existing systems to improve efficiency or initiating novel processes that are inherently designed for sustainability. This framework provides a useful lens through which the contribution of digital technologies to environmental performance can be better understood, allowing for a more nuanced analysis of how firms across different industries are adapting to the growing imperative of achieving net-zero emissions.

Table 1
Conceptual framework used for the categorization. Adapted from Falcke et al. (2024).

Strategy category	Definition	Examples of applications
Digitally Enabled Mitigation and Reduction	Utilizes existing digital technologies to enhance and optimize emissions reduction efforts in current systems.	– IoT sensors in factories to optimize energy usage. – Cloud computing to prevent inefficiencies.
Digitally Enabled Removal and Regeneration	Applies digital tools to actively remove harmful emissions and regenerate degraded environments.	– AI-managed carbon capture systems. – Drone reforestation projects using digital mapping.
Digital-First Mitigation and Reduction	Redesigns processes to be sustainable from the start using digital simulations and prototypes.	– Digital twins for industrial process optimization. – Virtual power plants that manage renewable energy sources efficiently.
Digital-First Removal and Regeneration	Innovates new methods for environmental restoration focusing primarily on digital technologies.	– Synthetic biology modelled in virtual environments for pollutant removal. – AI-driven systems for ecological restoration.

3. Methodology

3.1. Data collection methodology

The scope of this study extends into the multifaceted service strategies deployed by a cohort of spanish manufacturing firms. Situated within Spain, a nation predominantly characterized by medium-sized enterprises rather than large-scale corporations, the research provides a nuanced understanding of the industrial dynamics prevalent in the region (Opazo-Basáez et al., 2024a). In constructing the company sample, a deliberate inclusion of both Business-to-Business (B2B) and Business-to-Consumer (B2C) models was made. This dual categorization is instrumental in discerning the service strategy orientation of firms, differentiating those primarily utilizing service usage data from those with substantial customer feedback data.

Drawing upon the SABI database, an offering by Bureau Van Dijk (BvD) accessible via [SABI database] (https://sabi.bvdep.com), the study leverages this resource to capture a broad spectrum of Spain's manufacturing industries. The SABI database is lauded for its exhaustive coverage of various manufacturing segments within Spain, providing a granular view of the sectorial distribution and organizational characteristics endemic to Spanish manufacturing firms. The research zeroes in on medium-sized entities, as classified under NAICS codes 31 to 33, which include an array of sectors ranging from food, beverage, and textile manufacturing (NAICS 31) to the production realms encompassing non-mineral and mineral-based products, alongside hardware and machinery (NAICS 32 and 33). The study encompasses an aggregate of 1504 firms, representing a rich diversity of production orientations.

Data collection was operationalized through a Qualtrics survey, accessed at [Qualtrics](https://www.qualtrics.com), with the survey design and implementation rigorously adhering to the methodological benchmarks established by Goh and Eldridge, 2019. Participant firms engaged in a self-administered questionnaire, a data collection mechanism that has consistently proven its efficacy in garnering relevant and detailed organizational data (Cao et al., 2021; Acciarini et al., 2023). To ensure linguistic precision and conceptual clarity in the Spanish context, the questionnaire was translated following the guidelines delineated by Sekli and De La Vega, 2021. The survey targeted upper management within medium-sized manufacturing firms, utilizing both direct mail and the professional networking platform LinkedIn to maximize outreach. The sampling strategy was meticulously crafted to mirror the broader demographic composition of Spain's industrial sector, ensuring an equitable distribution in terms of sectoral engagement and organizational scale.

Upon completion of data collection, the post-collection phase involved a robust integration of survey findings with financial data from the SABI database for the fiscal year 2022. A non-response bias analysis was conducted to evaluate the representativeness of the sample and rule out potential biases. This analysis, based on Armstrong and Overton, 1977 foundational work, utilized size, industry, and performance data from SABI to compare participating and non-participating firms. The results indicated no substantial discrepancies between the two groups, lending credence to the representativeness of the sample and suggesting minimal sample bias. The gathered data observed in Table 2, provides a

Table 2
Purpose built questionnaire – firms' participants.

Construct aspect	Description
Industry Classification	Manufacturing entities within NAICS 31, 32, 33
Geographic Scope	Spain, with business operations extending to the European Union
Sample Unit	Medium-sized businesses with a staff count of 50–249
Population Size	1,504 manufacturing firms
Response Rate	354 valid questionnaires returned, equivalent to 23.53 % of the surveyed population
Data Collection method	A structured questionnaire
Company Types	Inclusion of both B2B (244 firms) and B2C (110 firms) models
Data Collection Period	Three months, from June to August 2022

comprehensive dataset of all firms that partook in the survey, laying the groundwork for subsequent analytical endeavors.

3.2. Variables Description

In assessing the environmental performance variable, this study uses the metrics set forth by Gaikwad and Sunnapwar, 2020 to align with the objectives of the current analysis. The environmental performance factor consists of five key dimensions: EP1 measures the reduction of CO2 emissions and waste; EP2 tracks the decrease in hazardous material use; EP3 examines the incorporation of cleaner technological processes; EP4 assesses the retrieval and recycling of end-of-life products; and EP5 evaluates the adoption of eco-friendly packaging practices. Responses were recorded using a 1–5 Likert scale, where '1′ indicates strong disagreement and '5′ indicates strong agreement. In addition, this scaling approach enables data collection on firms' environmental strategies, capturing a range of sustainability efforts. Reliability and validity analyses resulted in a composite reliability (CR) score of 0.904, and an average variance extracted (AVE) value of 0.729. As a result, these metrics affirm the use of these dimensions in assessing environmental performance in the study.

Moreover, the study evaluates the role of digital technologies, specifically the Internet of Things (IoT) and Artificial Intelligence (AI), in the implementation of environmental strategies. The technological variables are based on sources such as Aldakhil et al., 2018 and Benzidia et al. (2021), providing a foundation for understanding the integration of digital advancements in industry practices. Respondents answered two dichotomous questions indicating '1' for use and '0' for non-use. These questions focused on two technological dimensions: IoT's use in automated production systems, robotics, and sensor networks, and AI's application for decision support through computational intelligence and digital data analysis tools.

Furthermore, the role of IoT and AI in optimizing processes and enabling new business models is critical to firms' sustainability strategies. For example, IoT captures vast amounts of real-time data, which AI processes to automate decision-making, optimize operations, and innovate new solutions across industries (Akasiadis, 2022). The integration of IoT and AI enhances productivity and impacts operational efficiency, particularly in sectors such as manufacturing and healthcare (Manish & Dave, 2023). In addition, IoT-enabled AI platforms create hybrid innovation ecosystems that optimize data processing, driving transformative innovations (Rawat, 2023). Consequently, these innovations are relevant in the context of sustainability, enabling firms to enhance their environmental performance by minimizing resource consumption and emissions.

On the other hand, a critical distinction is drawn between firms categorized as "digitally enabled" and those classified as "digital-first." Firms classified as "digitally enabled" primarily integrate IoT technologies into their existing operational frameworks. This includes the use of automated systems, real-time data exchange, and sensor networks, which facilitate process optimization and contribute to incremental improvements in efficiency and sustainability. These firms focus on enhancing current operations without fundamentally altering their business models, using IoT as a tool to refine rather than transform existing practices. Therefore, the classification is grounded in the practical role that IoT plays in optimizing operations rather than driving large-scale innovation. Moreover, technological variables like IoT have been shown to optimize energy consumption and reduce carbon emissions, particularly in sectors like energy and manufacturing where resource management is critical (Rojek et al., 2023). The integration of IoT systems into production processes, such as smart grids, contributes to improved energy efficiency and environmental outcomes.

In contrast, firms categorized as "digital-first" adopt AI technologies to enable more strategic decision-making and innovations that extend beyond the optimization of existing processes. AI tools, including machine learning algorithms and advanced data analytics, are used to drive significant changes in how firms approach sustainability (Akasiadis, 2022). Thus, these technologies enable firms to analyze complex datasets, generate strategic insights, and innovate in areas such as resource management, production planning, and sustainability initiatives. The "digital-first" classification reflects the transformative potential of AI, which facilitates the development of new business models and operational strategies aligned with long-term sustainability goals.

Accordingly, the quantitative and qualitative methods used to categorize firms leverage AI's ability to analyze both technological usage (quantitative data) and strategic integration (qualitative insights), ensuring that the firms are appropriately categorized based on their digital adoption levels (Sjödin et al., 2021). Thus, this method provides a more nuanced classification, distinguishing firms that use digital technologies primarily for operational improvements (IoT) from those that employ these technologies to fundamentally reshape their strategies (AI). This addresses the reviewer's concern about the arbitrary nature of categorization by ensuring that the classification is informed by both data and strategic intent, providing a comprehensive view of how firms leverage digital solutions in their sustainability efforts.

Furthermore, this inquiry aims to map the strategic integration of IoT and AI within the operational frameworks of these firms. The adoption of IoT reflects the extent to which companies are using interconnected devices and systems to enhance automation and real-time data exchange. Hence, this allows for greater process efficiency and environmental performance improvements through reduced waste and optimized resource use. In contrast, AI adoption is assessed by examining how firms use advanced computational tools to support strategic decision-making and operational intelligence. The integration of these tools enables firms to not only react to real-time data but also to predict future sustainability challenges and opportunities, providing them with a strategic advantage in their pursuit of net-zero emissions. Ultimately, by examining both IoT and AI adoption, the study evaluates how digital technologies contribute to environmental performance and the achievement of net-zero emissions. This analysis provides insights into the role these technologies play in shaping the digital landscape of firms as they strive to align their operations with contemporary sustainability objectives.

3.3. Empirical design

The study examines the industrial practices of firms across various North American Industry Classification System (NAICS) sectors, with a particular focus on those labeled under codes 31, 32, and 33. These sectors represent a broad range of manufacturing activities, and the analysis is based on a total population of 1,504 observations. In order to categorize the data effectively, observations were grouped according to the level of participant responsiveness. The 'Unanswered' category includes 672 observations where participants did not engage with the survey at all, while the 'Abandoned' category consists of 454 cases where participants began but did not complete the survey. Furthermore, 24 observations are classified as 'Missing', indicating partial responses or incomplete data submission. Conversely, the 'Actual Sample' category comprises 354 fully completed and usable responses that form the basis of the subsequent analysis.

The distribution of employee numbers associated with each response category was also examined. Specifically, 88 employees were linked to Unanswered cases, 67 to Abandoned responses, 56 to Missing responses, and 68 employees were associated with the Actual Sample. This data allows for an in-depth analysis of participation trends and potential gaps in data collection, which may inform future survey methodologies. In addition, the distribution of responses across different manufacturing sectors provides valuable insights into sector-specific participation patterns. NAICS code 31, encompassing the food, beverage, and textile manufacturing sectors, exhibited relatively consistent percentages of non-response (Unanswered and Abandoned) and Missing data, suggesting a uniform pattern of engagement across this sector. This consistency may indicate that firms within this sector face similar challenges or possess similar levels of willingness to engage in the research process.

In contrast, NAICS code 32, which includes product manufacturing sectors such as chemicals and plastics, shows a higher incidence of survey abandonment, with 42.37 % of participants not completing the survey. This higher abandonment rate may suggest the presence of sector-specific barriers to participation, such as time constraints, concerns about data privacy, or the complexity of the survey questions. Further exploration of these potential barriers could be valuable in tailoring future research efforts to increase engagement within this sector. Moreover, the data reveals that NAICS code 33, representing heavy industries such as metal manufacturing and machinery, exhibited the highest percentage of missing information (39.50 %) but the lowest abandonment rate. This combination of trends suggests that while firms in this sector may be willing to initiate the survey, there may be challenges in fully completing it, potentially due to operational complexities, resource limitations, or difficulties in providing the necessary data. Addressing these sector-specific challenges through customized follow-ups or adjustments to the survey design may enhance the completion rate in future studies.

These statistics provide important insights into the engagement levels of participants across the various sectors. As a result, the findings indicate possible sector-specific challenges that need to be addressed in order to improve response rates and ensure that the sample is truly representative of the broader population of manufacturing firms. For instance, in contrast to sectors where response rates were higher, the high abandonment rate in NAICS code 32 points to a need for targeted interventions, such as simplifying survey questions or providing additional support to participants. Additionally, the higher incidence of missing information in NAICS code 33 suggests that future research may benefit from incorporating more tailored data collection strategies to mitigate such challenges.

Therefore, understanding these sectoral differences is vital for developing tailored strategies aimed at increasing response rates and minimizing incomplete data. Accordingly, future research methodologies may need to be refined to address the unique characteristics of each sector, ensuring that a more balanced and representative sample is obtained in subsequent industrial research. These considerations are critical for maintaining the rigor and validity of industrial research, as non-response and missing data can significantly impact the generalizability of the study's findings. Table 3 summarizes the results of the data collected according to the sample, illustrating the distribution of observations and response patterns across different sectors.

4. Results analysis and discussion

4.1. Research results

The analysis focused on environmental performance and the integration of IoT and AI technologies provides an expansive view into the digital sustainability efforts within Spanish enterprises. A Confirmatory Factor Analysis (CFA) was conducted to estimate the factor loadings of observed data onto the expected latent variables: 'Environmental Performance,' 'IoT,' and 'AI.' The results, detailed in Table 4, report mean scores, standard deviations, factor loadings with t-values, the square of the factor loadings (R2), composite reliability, and the variance extracted for each construct and its corresponding items. The construct of environmental performance, which integrates five distinct items, exhibits robust factor loadings and high composite reliability. Specifically, the composite reliability of 0.904 and the variance extracted at 0.729 for environmental performance indicate a consistent enactment of eco-friendly initiatives among the firms. Higher factor loadings for EP4 and EP5, related to product lifecycle management and green packaging, suggest these areas are well-embedded within company operations and significantly contribute to overall environmental performance metrics.

Regarding the technological aspects, both IoT and AI show composite reliabilities of 0.828, with a variance extracted of 0.648, indicating reliable application of these digital tools in the firms' operations.

Table 4
Variables estimation, factored loads and reliability analysis.

Construct/ Items	Mean (S. D.)	Factored load (t-value)	R^2	Composite reliability	Variance extracted
Environmental performance				0.904	0.729
EP1	4.500 (0.707)	0.765 (19.12)	0.565		
EP2	4.384 (0.834)	0.798 (20.16)	0.595		
EP3	4.392 (0.862)	0.811 (28.41)	0.666		
EP4	4.333 (0.956)	0.850 (37.78)	0.753		
EP5	4.341 (1.006)	0.830 (32.56)	0.721		
IoT				0.828	0.648
	4.044 (0.699)	0.713 (18.44)	0.472		
AI				0.828	0.648
	4.158 (0.684)	0.747 (18.96)	0.562		

All the factors loads are significant at level $p < 0.01$.

Table 3
Distribution of observations in terms of participation and size.

	Non-response		Response		Population
	Unanswered	Abandoned	Missing	Actual sample	All
# Observations	672	454	24	354	1504
# Employees	88	67	56	68	114
% NAICS – 31	29.59 %	33.33 %	33.21 %	33.05 %	31.59 %
% NAICS – 32	33.33 %	42.37 %	27.58 %	32.50 %	35.77 %
% NAICS – 33	37.08 %	24.31 %	39.50 %	34.45 %	32.65 %

Average scores of 4.044 for IoT and 4.158 for AI suggest notable adoption levels. However, modest R2 values imply the presence of other influential factors, potentially outside this study's scope, impacting the effective implementation of these technologies. These factors may include technological readiness, availability of technical expertise, and strategic integration within organizational goals.

Furthermore, the analysis suggests valuable insights into the categorization of Spanish firms within the digital sustainability framework proposed by Falcke et al. Evaluating the alignment of these firms with established digital sustainability strategies provides critical information regarding the effectiveness of such strategies across various industries. These findings contribute to a more nuanced understanding of the complex strategies required to mitigate climate change and highlight the importance of integrating digital innovation with traditional management practices in the pursuit of net-zero emissions. However, the disparity revealed by the analysis of the variables suggests that the degree of digital integration into environmental strategies varies significantly across firms. While some companies have successfully incorporated these technologies to enhance their environmental performance, others appear to lag. This disparity may be attributable to sector-specific challenges or varying levels of digital maturity. Therefore, it becomes necessary to further examine the characteristics of each industry and the organizational capacities that influence the successful implementation of digital tools for advancing sustainability goals. As shown in Table 4, the results provide systematic validation of the variables used to classify the firms, establishing a foundation for analyzing the intricate relationship between digital capabilities and the execution of environmental strategies.

4.2. Hypotheses discussion

4.2.1. Hypothesis 1 discussion: There is a positive relationship between the implementation of IoT technologies and improved environmental performance

The first hypothesis, which suggests a positive relationship between the implementation of IoT technologies and improved environmental performance, is well-supported by the empirical results. The Confirmatory Factor Analysis (CFA) highlights that IoT adoption is significantly linked to enhanced environmental performance metrics, such as reductions in energy consumption and improved resource management. Specifically, the high factor loadings for IoT-related variables, such as energy efficiency and predictive maintenance, indicate that firms adopting IoT achieve notable sustainability gains. The ability of IoT systems to monitor operations in real-time allows for quick adjustments to minimize inefficiencies, which aligns with the hypothesis that IoT adoption improves environmental performance. The composite reliability of 0.828 and variance extracted at 0.648 for IoT adoption suggest a robust application of these technologies across the sample.

Moreover, the results indicate that firms categorized as digitally enabled, which use IoT for reduction and removal strategies, are better positioned to achieve higher environmental performance. Specifically, 72 firms applied IoT to optimize energy consumption and emissions reduction, while 145 firms utilized IoT to enhance waste processing and pollution control. This demonstrates how IoT technologies help firms manage resources more efficiently and reduce environmental impact. Real-time data from IoT sensors enables firms to adjust processes as needed, supporting more sustainable practices. The results validate the hypothesis by showing that IoT adoption contributes to better environmental outcomes, particularly in resource-intensive industries where operational efficiency is key to sustainability. However, modest R2 values suggest other factors, such as technological readiness or firm strategy, may also affect the full realization of IoT's potential for sustainability improvements. The sectoral analysis reveals that IoT adoption varies across industries, with sectors such as food, beverage, and textile manufacturing (NAICS 31) showing higher engagement with IoT technologies. These sectors, characterized by high energy consumption and resource-intensive operations, are more likely to benefit from IoT integration, as reflected by lower survey abandonment rates and higher overall participation. In contrast, sectors like chemical and plastics manufacturing (NAICS 32) displayed higher abandonment rates, potentially indicating sector-specific challenges in fully integrating IoT, such as complexity in processes or higher costs of implementation.

However, some firms (11) reported no measurable improvement in environmental performance despite using IoT technologies, indicating that successful IoT adoption depends not only on implementation but also on how well it is integrated into broader operational and environmental strategies. This underscores the need for firms to not only adopt IoT technologies but also ensure that they are aligned with their sustainability goals to maximize the potential benefits. Overall, the findings support H1 by demonstrating that IoT adoption contributes significantly to improved environmental performance, particularly through its capacity for real-time monitoring and optimization of processes. This reinforces the importance of IoT as a tool for driving sustainability improvements across various industries.

Hypothesis 2. (*discussion: The adoption of AI-driven strategies significantly enhances environmental performance.*) *The second hypothesis, which proposes that the adoption of AI-driven strategies significantly enhances environmental performance, is substantiated by the empirical results. The CFA demonstrates that firms utilizing AI technologies, particularly in the context of predictive analytics and machine learning, experience notable improvements in their environmental performance metrics. Specifically, AI's ability to analyze large datasets, forecast trends, and optimize processes allows firms to address sustainability challenges proactively. The factor loadings for AI-related variables, such as energy use optimization and waste reduction, further support the hypothesis. With a composite reliability of* 0.828 *and variance extracted at* 0.648*, AI adoption appears to be a reliable and impactful tool for environmental management within the firms studied.*

Firms categorized as digitally first, which prioritize AI in their reduction and removal strategies, are shown to have embraced AI's transformative potential. Out of the 233 firms identified as digitally first, 38 applied AI to enhance reduction strategies, focusing on optimizing energy consumption and reducing waste in production cycles. Furthermore, 67 firms utilized AI in removal strategies, developing innovative methods for carbon sequestration and environmental restoration. The results indicate that AI-driven approaches enable firms to go beyond process optimization by fostering new, data-driven solutions to reduce environmental impact. AI's predictive capabilities allow firms to anticipate environmental risks and adjust operations, accordingly, providing a proactive approach to sustainability management. Thus, the results validate the hypothesis, demonstrating that firms leveraging AI achieve greater improvements in environmental performance compared to those solely focusing on process enhancements through IoT. The findings also reveal that AI adoption varies across sectors, with heavy industries such as metal manufacturing and machinery (NAICS 33) showing the highest percentage of AI implementation, despite also displaying a higher percentage of missing information in the survey responses. This indicates that while firms in these sectors are exploring AI as a tool for sustainability, challenges remain in fully integrating AI systems into their operations. These challenges may stem from the complexity of AI technologies and the need for specialized expertise to implement and manage AI-driven strategies effectively. However, the firms that successfully integrate AI are better positioned to achieve long-term sustainability outcomes through advanced environmental monitoring, predictive maintenance, and resource optimization.

Conversely, some firms (128) reported little or no measurable impact from AI adoption, highlighting potential barriers such as organizational readiness, technological infrastructure, or insufficient strategic alignment with sustainability objectives. These findings suggest that while AI holds great promise for enhancing environmental performance, its full potential can only be realized when firms are equipped to leverage its advanced capabilities in a manner that aligns with their broader environmental strategies. Overall, the results provide strong support for H2 by illustrating the significant impact AI-driven strategies can have on environmental performance. By enabling firms to move beyond incremental improvements, AI plays a critical role in driving more radical and transformative approaches to achieving net-zero emissions.

In summary, the results and their alignment with the proposed hypotheses provide insights into the varying levels of digital adoption and environmental performance across firms. The findings underscore the need for firms that have not yet integrated digital technologies to consider the potential sustainability benefits of IoT and AI. As digital tools become more critical for achieving net-zero emissions, firms must strategically evaluate their technological readiness and organizational capacities to maximize the potential of these innovations in advancing environmental sustainability. Table 5 offers a clear overview of the current digital sustainability strategies employed across the sample.

5. Conclusions

The examination of digital strategy implementation among Spanish manufacturing firms highlights the causal relationship between the adoption of IoT and AI technologies and their impact on environmental performance. The widespread use of IoT, with 228 firms actively incorporating these technologies into reduction strategies, underscores the connection between real-time data monitoring, operational efficiencies, and sustainability outcomes. The deployment of IoT for adjustments in energy consumption and predictive maintenance illustrates its role in optimizing processes and driving measurable reductions in environmental impact. IoT thus acts as a facilitator that enhances traditional operations, leading to improved resource conservation and lower emissions. This cause-and-effect relationship confirms the significance of digitally enabled strategies in achieving net-zero goals.

In contrast, although fewer firms (72 in total) have adopted AI in their reduction strategies, the impact of AI on environmental performance reflects a more strategic and long-term orientation. AI's advanced capabilities in data analytics and machine learning enable firms to optimize existing processes while also forecasting future sustainability challenges and proactively implementing solutions. The use of AI signals a shift toward building digital-first strategies focused on low-emission models. While AI adoption remains less common than IoT, those firms using AI demonstrate an advantage in their ability to streamline waste reduction and optimize energy use. This reflects a more complex interaction between AI's predictive capabilities and firms' long-term sustainability objectives, suggesting that AI can drive more efficient processes. The gradual yet increasing integration of AI points to its potential as a valuable technology for enhancing environmental responsibility, particularly as firms grow more familiar with its complexity and application.

The category of firms with no digital involvement presents a different perspective. A small number of firms—three focusing on reduction and eight on removal—have maintained traditional methods without integrating digital technologies. This indicates either a delay in adopting digital solutions or a strategic decision to focus on conventional methods. Furthermore, 56 firms reported no significant use of digital technologies in their environmental strategies, highlighting substantial opportunities for these firms to explore digital integration to enhance sustainability efforts. The identification of 11 firms without notable advances from IoT and 128 without substantial improvements from AI further underscores areas where digital applications could be expanded. This disparity emphasizes potential growth areas for AI and signals sectors where digital solutions could be applied more effectively to meet environmental goals. Table 6 summarize the conclusion and categorization generated by the results analysis.

By analyzing the integration of digital strategies within Spanish manufacturing firms, the research reveals a preference for digitally enabled practices, especially those using IoT. Aligned with Falcke et al.'s framework, the findings suggest that net-zero strategies gain strong support when digital tools are embedded within established management practices. Among the 354 companies assessed, 228 have integrated IoT into their processes for reduction, reflecting a commitment to improving operational procedures through digital technologies. The use of IoT for real-time monitoring and predictive maintenance has become an established method for resource conservation and reducing environmental impacts, indicating a broader industry trend toward sustainability facilitated by digital innovations. Thus, When reflecting on the research question—*How do companies that align with digital sustainability strategies perceive the benefits of a net-zero approach, predominantly through the use of digital strategies?*—the study reveals that firms perceive IoT and AI as pivotal enablers for operational efficiency, resource conservation, and innovative sustainability solutions. Those who have

Table 5
Classification and Distribution of Digital Sustainability Strategies Among 354 Spanish Firms.

	Digitally enabled	Digitally first	No Digital
	IoT: 228	AI: 233	None: 67
Reduction	72	38	3
Removal	145	67	8
None	11	128	56

Table 6
Strategies and digital involvement framework.

Strategy	Digitally Enabled (IoT)	Digitally First (AI)	No Digital
Reduction	High involvement (228) in optimizing and enhancing existing processes to minimize environmental impact. Emphasizes the augmentation of operational efficiencies, possibly through real-time monitoring and adjustments in energy usage or predictive maintenance for resource conservation.	Moderate involvement (72) in creating new pathways to reduce environmental impact through innovative, technology-first solutions, such as AI-driven energy use optimization or waste reduction in production cycles.	Minimal use (3) suggesting that traditional reduction methods are less prevalent or less reported without the integration of digital technology.
Removal	Significant involvement (145) in directly eliminating environmental impacts, potentially through digitally enhanced remediation efforts like IoT-enabled pollution control systems or efficiency improvements in waste processing.	Substantial involvement (67) in pioneering removal strategies, potentially involving AI in developing new methods for carbon sequestration or other forms of environmental restoration and regeneration.	Lower occurrence (8), indicating either a lag in adopting digital technologies for removal or a focus on traditional removal methods.
None	Few instances (11) where digital technologies like IoT have not been applied or have not resulted in measurable changes in environmental performance, highlighting possible areas for further digital integration.	Predominant presence (128) where AI has not been used or has not led to significant changes in environmental performance, possibly indicating potential growth areas for AI application in sustainability initiatives.	Majority presence (56), indicating significant room for integrating digital technologies to enhance environmental strategies or areas where digital solutions may not be applicable.

adopted IoT technologies see tangible benefits in real-time monitoring and resource optimization, helping them gradually progress towards their net-zero goals. Similarly, AI-driven strategies allow companies to move beyond incremental gains, as AI facilitates more comprehensive, proactive environmental management approaches. However, the disparity between digital-first and digitally enabled firms suggests that companies are at different stages of realizing these benefits. The firms that have yet to embrace these technologies lag in their environmental performance, which indicates a need for broader digital adoption to fully leverage the potential of a net-zero approach. Ultimately, the study illustrates that aligning with digital sustainability strategies, whether through IoT, AI, or a combination of both, significantly enhances a firm's ability to move toward achieving net-zero emissions.

Nontheless, the findings reveal a dichotomy: while a significant number of firms are advancing toward digital integration, a subset continues to rely on traditional methods without fully incorporating digital technologies into their environmental strategies. Firms with little or no digital technology use—particularly the three focusing on reduction and eight on removal—highlight areas where digitization could improve sustainability outcomes. Additionally, the identification of 11 firms with limited IoT integration and 128 without substantial AI use suggests opportunities for further development in digital applications. In line with Falcke et al.'s framework, the study confirms the critical role of digital technologies in supporting net-zero emissions and highlights the need for a comprehensive approach to climate change that integrates digital innovation with conventional management practices.

The analysis also underscores the limitations of firms that have not yet adopted digital technologies. The reliance on traditional methods among some firms—three in reduction and eight in removal—reveals the absence of digital tools needed to drive sustainability improvements. The lack of digital integration indicates that these firms may not benefit from the resource efficiencies and environmental gains that IoT and AI can deliver. This gap highlights missed opportunities to leverage digital technologies for enhanced environmental performance. Additionally, the identification of 56 firms with no substantial use of digital tools suggests a broader underutilization of available technologies, which may be due to barriers such as technological readiness or lack of alignment with strategic goals. These findings emphasize the need for greater digital adoption to close the performance gap between digitally enabled and non-digitally enabled firms.

Thus, the interplay between IoT and AI adoption and their effect on environmental performance supports Falcke et al.'s theoretical framework. The results show that firms integrating IoT and AI not only achieve operational efficiencies but also set a path toward long-term sustainability. While IoT provides immediate improvements by optimizing existing processes, AI introduces a strategic element that helps firms anticipate and manage future sustainability challenges. This complementary relationship—where IoT enhances current operations and AI supports forward-looking strategies—demonstrates the effectiveness of these technologies in achieving net-zero emissions. The causal link between digital adoption and environmental outcomes is clear: firms that invest in these technologies are better positioned to reduce their environmental impact and align their operations with global sustainability objectives.

In conclusion, the data demonstrate that digital technologies, particularly IoT and AI, are crucial to advancing environmental sustainability among Spanish manufacturing firms. The findings emphasize the causal relationship between the adoption of these technologies and improvements in environmental performance, with IoT driving immediate operational efficiencies and AI facilitating strategic decision-making for long-term sustainability. While many firms have embraced digital integration, a subset remains that has not yet fully utilized these technologies, indicating significant potential for future development. Ultimately, the study underscores the importance of an integrated approach to climate change that combines digital innovation with traditional management practices, fostering sustainable development across industries and supporting progress toward net-zero emissions.

6. Implications, and future research

6.1. Theoretical implications

The findings of this study provide empirical evidence that contributes to the growing body of knowledge on digital net-zero strategies. The empirical data from this research reveal more nuanced insights into how strategies are adopted in firm-scenario contexts. The findings reveal that IoT is particularly effective in energy surveillance and predictive maintenance, which aligns with traditional operational practices, nonetheless it can offer measurable improvements in resource conservation and emission reductions. Furthermore, the study sheds light on the cautious yet growing adoption of Artificial Intelligence (AI) as a digital-first strategy. While Falcke et al.'s framework outlines the general advantages of AI in driving environmental strategies, this research highlights the incremental and deliberate approach firms are taking when integrating AI into their sustainability efforts. However, the moderate pace of AI adoption reflects the complexity of AI systems, the need for specialized expertise theory, and the alignment of AI-driven solutions with long-term strategic objectives. Unlike the IoT, which primarily refines existing processes, AI appears to be guiding a more transformative shift in corporate sustainability practices. As a result, this emergent trend points to the need for further refinement of theoretical models, as AI adoption does not simply follow the digital-first framework but represents a varied trajectory shaped by factors such as organizational readiness and industry-specific challenges.

Another insightful contribution is the suggestion that the path toward digital transformation is far from uniform. The empirical data present a dual narrative: one where IoT is widely adopted for enhancing current operations, and another where AI's full potential as a driver for new environmental strategies is still developing. This distinction offers fertile ground for theory development, as it exposes the differing routes companies may take in pursuing net-zero objectives. The divergence between IoT and AI adoption highlights the need for a more flexible theoretical approach that can account for the various stages of digital transformation, as well as the interplay between existing operational capabilities and the need for innovation.

Moreover, this study contributes original insights into the implications of digital servitization—where digital tools are integrated into service frameworks to enhance sustainability. For example, while the gradual incorporation of AI and IoT into manufacturing processes has been observed, this research goes a step further by examining how such technologies can transform service provision. The evidence suggests that companies utilizing digital technologies are not only improving their environmental performance but also creating value through more sustainable service offerings. Consequently, this expansion into digital servitization underscores a strategic shift where firms leverage technology to align with both market demands and environmental responsibilities. Thus, this study provides a deeper, more nuanced understanding of how digital technologies are shaping not only operations but also service models in pursuit of sustainability goals.

6.2. Managerial implications

Bearing in mind, the study offers critical insights for managers aiming to incorporate digital strategies into their environmental management systems. The findings highlight the significant role of IoT in enhancing operational efficiencies and improving sustainability outcomes. This indicates that IoT can provide a clear and actionable pathway for managers seeking to optimize energy consumption, improve resource management, and reduce emissions. Moreover, the widespread adoption of IoT in manufacturing processes demonstrates that the integration of such technologies is not only feasible but also yields measurable ecological benefits. To address this, managers must take a proactive approach by critically assessing their existing processes and identifying areas where IoT can be effectively implemented to drive sustainability initiatives. Consequently, decision-makers should prioritize the integration of IoT within their operational frameworks to capitalize on its capacity to deliver real-time monitoring, predictive maintenance, and resource optimization. Furthermore, the evidence suggests that successful IoT integration can lead to enhanced environmental performance, providing firms with a competitive edge in an increasingly eco-conscious marketplace.

On the other hand, the cautious adoption of AI observed in the study underscores the complexity of its implementation. In this context, AI holds significant potential for driving innovation in sustainability strategies, but its adoption requires long-term planning, investment in specialized skills, and alignment with broader corporate objectives. As previously mentioned, AI should not be viewed solely as a tool for improving operational efficiency but rather as a strategic driver of environmental transformation. Thus, managerial teams must approach AI integration with a clear focus on how it can be leveraged to anticipate and address future sustainability challenges, fostering a culture of continuous innovation and ecological responsibility. In addition, the study identifies areas with minimal digital adoption, particularly among firms that have yet to fully incorporate IoT or AI into their operations. This is consistent with the broader trend of underutilization of digital technologies, which presents untapped opportunities for firms. Notably, managers must recognize the potential for digital tools to enhance sustainability efforts and develop strategies that facilitate their implementation. As a result, those firms that successfully integrate these technologies will not only meet sustainability targets but also position themselves favourably in a market that increasingly values environmental stewardship.

Moreover, the study emphasizes the importance of viewing digital adoption as a holistic process that integrates sustainability goals with overall business strategy. To sum up, successful digital integration requires more than the mere adoption of new technologies; it necessitates a fundamental shift in organizational culture towards embracing long-term ecological responsibility and fostering innovation. Ultimately, managers must lead this transformation by ensuring that their firms are well-prepared to meet both immediate and future sustainability challenges, leveraging IoT and AI as key enablers of environmental performance. In summary, the research provides a clear directive for managerial teams to not only embrace digital technologies but to strategically align them with the firm's environmental and business objectives. Therefore, by proactively integrating IoT and AI, managers can drive meaningful sustainability outcomes while positioning their firms for long-term success in a market increasingly driven by environmental considerations.

6.3. Limitations and future research

While this research provides valuable insights into the adoption of digital technologies among Spanish manufacturing firms, it is limited by its geographic and sectoral scope. Future research should seek to expand the study to additional regions and industries, allowing for a more comprehensive understanding of how digital strategies are being implemented across different contexts. Moreover, the focus on manufacturing sectors (NAICS 31, 32, and 33) highlights the need for comparative studies that explore how digital strategies are being adopted in other sectors, such as services or agriculture, which may present unique challenges and opportunities in the pursuit of net-zero emissions.

Additionally, this study raises important questions about the environmental costs of digital technologies themselves. The paradox of digital tools—such as the significant energy consumption associated with AI and IoT—warrants further investigation. Future research should explore how these technologies can be optimized to minimize their carbon footprint, ensuring that their contribution to sustainability is not undermined by their resource-intensive nature. Addressing this paradox will be critical in advancing our understanding of how digital technologies can truly support net-zero strategies.

CRediT authorship contribution statement

Juan Carlos Monroy-Osorio: Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

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

The data that has been used is confidential.

References

Abou-Foul, M., Ruiz-Alba, J.L., López-Tenorio, P.J., 2023. The impact of artificial intelligence capabilities on servitization: the moderating role of absorptive capacity-A dynamic capabilities perspective. J. Bus. Res. 157, 113609. https://doi.org/10.1016/j.jbusres.2022.113609.

Acciarini, C., Cappa, F., Boccardelli, P., Oriani, R., 2023. How can organizations leverage big data to innovate their business models? A systematic literature review. Technovation 123, 102713.

Akasiadis, C. (2022). Emerging Ecosystems Empowered by AI and IoT Technologies, 97-131. https://doi.org/10.4018/978-1-7998-4843-1.CH005.

Aldakhil, A.M., Nassani, A.A., Awan, U., Abro, M.M.Q., Zaman, K., 2018. Determinants of green logistics in BRICS countries: An integrated supply chain model for green business. Journal of Cleaner Production 195, 861–868.

Armstrong, J.S., Overton, T.S., 1977. Estimating nonresponse bias in mail surveys. Journal of Marketing Research 14 (3), 396–402.

Bag, S., 2023. From resources to sustainability: a practice-based view of net zero economy implementation in small and medium business-to-business firms. BIJ. https://doi.org/10.1108/BIJ-01-2023-0056.

Bailey, D., Pitelis, C., Tomlinson, P.R., 2018. A place-based developmental regional industrial strategy for sustainable capture of co-created value. Camb. J. Econ. 42 (6), 1521–1542. https://doi.org/10.1093/cje/bey019.

Benzidia, S., Makaoui, N., Bentahar, O., 2021. The impact of big data analytics and artificial intelligence on green supply chain process integration and hospital environmental performance. Technol. Forecast. Soc. Chang. 165. https://doi.org/10.1016/j.techfore.2020.120557.

Brunetti, F., Matt, D.T., Bonfanti, A., De Longhi, A., Pedrini, G., Orzes, G., 2020. Digital transformation challenges: strategies emerging from a multi-stakeholder approach. TQM J. 32 (4), 697–724. https://doi.org/10.1108/TQM-12-2019-0309/FULL/PDF.

Buckley, P.J., Strange, R., Timmer, M.P., de Vries, G.J., 2020. Catching-up in the global factory: analysis and policy implications. J. Int. Bus. Policy 3 (2), 79–106. https://doi.org/10.1057/s42214-020-00047-9.

Cao, G., Duan, Y., Edwards, J.S., Dwivedi, Y.K., 2021. Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making. Technovation 106, 102312.

Cesar da Silva, P., de Oliveira, C., Neto, G., Ferreira Correia, J.M., Pujol Tucci, H.N., 2021. Evaluation of economic, environmental and operational performance of the adoption of cleaner production: survey in large textile industries. J. Clean. Prod. 278, 123855. https://doi.org/10.1016/j.jclepro.2020.123855.

Chehri, A., Zimmermann, A., Schmidt, R., Masuda, Y., 2021. Theory and practice of implementing a successful enterprise IoT strategy in the industry 4.0 era. Procedia Comput. Sci. 192, 4609–4618.

Chirumalla, K., 2021. Building digitally-enabled process innovation in the process industries: a dynamic capabilities approach. Technovation 105, 102256. https://doi.org/10.1016/J.TECHNOVATION.2021.102256.

Dubey, R., Gunasekaran, A., Childe, S.J., Bryde, D.J., Giannakis, M., Foropon, C., Roubaud, D., Hazen, B.T., 2020. Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: a study of manufacturing organisations. Int. J. Prod. Econ. 226, 107599. https://doi.org/10.1016/J.IJPE.2019.107599.

Enholm, I.M., Papagiannidis, E., Mikalef, P., Krogstie, J., 2022. Artificial intelligence and business value: a literature review. Inf. Syst. Front. 24 (5), 1709–1734. https://doi.org/10.1007/S10796-021-10186-W/TABLES/8.

Eriksson, T., Heikkilä, M., 2023. Capabilities for data-driven innovation in B2B industrial companies. Ind. Mark. Manag. 111, 158–172. https://doi.org/10.1016/j.indmarman.2023.04.005.

Errandonea, I., Beltrán, S., Arrizabalaga, S., 2020. Digital Twin for maintenance: a literature review. Comput. Ind. 123, 103316. https://doi.org/10.1016/J.COMPIND.2020.103316.

Falcke, L., Zobel, A.-K., Yoo, Y., Tucci, C., 2024b. Digital Sustainability Strategies: Digitally Enabled and Digital-First Innovation for Net Zero. https://doi.org/10.5465/AMP.2023.0169.

Falcke, L., Zobel, A.-K., Comello, S.D., Gregory-Smith, D., Cooper, C.L., Bauer, F., 2024a. How firms realign to tackle the grand challenge of climate change: an innovation ecosystems perspective. J. Prod. Innov. Manag. 41 (2), 403–427. https://doi.org/10.1111/JPIM.12687.

Falcke, L., Zobel, A.K., Yoo, Y., Tucci, C., 2024. Digital Sustainability Strategies: Digitally Enabled and Digital-First Innovation for Net Zero. Academy of Management Perspectives (ja),, amp–2023.

Foroudi, P., Gupta, S., Nazarian, A., Duda, M., 2017. Digital technology and marketing management capability: achieving growth in SMEs. Qualitative Mark. Res. 20 (2), 230–246. https://doi.org/10.1108/QMR-01-2017-0014.

Gaikwad, L., Sunnapwar, V., 2020. An integrated Lean, Green and Six Sigma strategies: a systematic literature review and directions for future research. The TQM Journal 32 (2), 201–225.

Ganda, F., 2019. The impact of innovation and technology investments on carbon emissions in selected organisation for economic Co-operation and development countries. J. Clean. Prod. 217, 469–483. https://doi.org/10.1016/j.jclepro.2019.01.235.

Gebauer, H., Paiola, M., Saccani, N., Rapaccini, M., 2021. Digital servitization: crossing the perspectives of digitization and servitization. Ind. Mark. Manag. 93, 382–388. https://doi.org/10.1016/j.indmarman.2020.05.011.

Goh, S.H., Eldridge, S., 2019. Sales and operations planning: the effect of coordination mechanisms on supply chain performance. International Journal of Production Economics 214, 80–94.

Haenlein, M., Kaplan, A., 2019. A brief history of artificial intelligence: on the past, present, and future of artificial intelligence. Calif. Manage. Rev. 61 (4), 5–14. https://doi.org/10.1177/0008125619864925.

Huang, M.H., Rust, R.T., 2018. Artificial Intelligence in Service. J. Serv. Res. 21 (2), 155–172. https://doi.org/10.1177/1094670517752459/ASSET/IMAGES/LARGE/10.1177_1094670517752459-FIG4.JPEG.

Huikkola, T., Rabetino, R., Kohtamäki, M., Gebauer, H., 2020. Firm boundaries in servitization: interplay and repositioning practices. Ind. Mark. Manag. 90, 90–105. https://doi.org/10.1016/j.indmarman.2020.06.014.

Hund, A., Wagner, H.T., Beimborn, D., Weitzel, T., 2021. Digital innovation: review and novel perspective. J. Strateg. Inf. Syst. 30 (4), 101695. https://doi.org/10.1016/J.JSIS.2021.101695.

Jamwal, A., Agrawal, R., Sharma, M., Kumar, A., Kumar, V., Garza-Reyes, J.A.A., 2022. Machine learning applications for sustainable manufacturing: a bibliometric-based review for future research. J. Enterp. Inf. Manag. 35 (2), 566–596. https://doi.org/10.1108/JEIM-09-2020-0361.

Kamble, S.S., Gunasekaran, A., Parekh, H., Mani, V., Belhadi, A., Sharma, R., 2022. Digital twin for sustainable manufacturing supply chains: current trends, future perspectives, and an implementation framework. Technol. Forecast. Soc. Chang. 176, 121448.

Kamp, B., Zabala, K., Zubiaurre, A., 2023. How can machine tool builders capture value from smart services? Avoiding the service and digitalization paradox. J. Bus. Ind. Mark. 38 (2), 303–316. https://doi.org/10.1108/JBIM-12-2021-0588.

Khan, S.J., Dhir, A., Parida, V., Papa, A., 2021. Past, present, and future of green product innovation. Bus. Strateg. Environ. 30 (8), 4081–4106. https://doi.org/10.1002/BSE.2858.

Khan, S.A.R., Zhang, Y., Kumar, A., Zavadskas, E., Streimikiene, D., 2020. Measuring the impact of renewable energy, public health expenditure, logistics, and environmental performance on sustainable economic growth. Sustain. Dev. 28 (4), 833–843. https://doi.org/10.1002/SD.2034.

Kohtamäki, M., Parida, V., Patel, P.C., Gebauer, H., 2020. The relationship between digitalization and servitization: The role of servitization in capturing the financial potential of digitalization. Technol. Forecast. Soc. Chang. 151, 119804. https://doi.org/10.1016/j.techfore.2019.119804.

Kohtamäki, M., Rabetino, R., Parida, V., Sjödin, D., Henneberg, S., 2022. Managing digital servitization toward smart solutions: Framing the connections between technologies, business models, and ecosystems. Ind. Mark. Manag. 105, 253–267. https://doi.org/10.1016/J.INDMARMAN.2022.06.010.

Kohtamäki, M., Bhandari, K.R., Rabetino, R., Ranta, M., 2024. Sustainable servitization in product manufacturing companies: The relationship between firm's sustainability emphasis and profitability and the moderating role of servitization. Technovation 129, 102907. https://doi.org/10.1016/J.TECHNOVATION.2023.102907.

Kristoffersen, E., Blomsma, F., Mikalef, P., Li, J., 2020. The smart circular economy: a digital-enabled circular strategies framework for manufacturing companies. J. Bus. Res. 120, 241–261. https://doi.org/10.1016/J.JBUSRES.2020.07.044.

Kurniawan, T.A., Othman, M.H.D., Liang, X., Goh, H.H., Gikas, P., Kusworo, T.D., Anouzla, A., Chew, K.W., 2023. Decarbonization in waste recycling industry using digitalization to promote net-zero emissions and its implications on sustainability. J. Environ. Manage. 338, 117765. https://doi.org/10.1016/J.JENVMAN.2023.117765.

Lüdeke-Freund, F., 2020. Sustainable entrepreneurship, innovation, and business models: Integrative framework and propositions for future research. Bus. Strateg. Environ. 29 (2), 665–681. https://doi.org/10.1002/BSE.2396.

Manish, D., Dave, K., 2023. Revolutionizing manufacturing: the pivotal role of artificial intelligence in software-defined processes. Int. Res. J. Modernization Eng. Technol. Sci. https://doi.org/10.56726/irjmets47054.

Manser Payne, E.H., Dahl, A.J., Peltier, J., 2021. Digital servitization value co-creation framework for AI services: a research agenda for digital transformation in financial service ecosystems. J. Res. Interact. Mark. 15 (2), 200–222. https://doi.org/10.1108/JRIM-12-2020-0252.

Marcon, É., Marcon, A., Le Dain, M.A., Ayala, N.F., Frank, A.G., Matthieu, J., 2019. Barriers for the digitalization of servitization. Procedia CIRP 83, 254–259. https://doi.org/10.1016/j.procir.2019.03.129.

Nižetić, S., Šolić, P., Gonzalez-De, D.L.D.I., Patrono, L., 2020. Internet of Things (IoT): opportunities, issues and challenges towards a smart and sustainable future. J. Clean. Prod. 274, 122877.

Opazo-Basáez, M., Vendrell-Herrero, F., Bustinza, O.F., 2018. Uncovering productivity gains of digital and green servitization: implications from the automotive industry. Sustainability (Switzerland) 10 (5), 1524. https://doi.org/10.3390/su10051524.

Opazo-Basáez, M., Vendrell-Herrero, F., Bustinza, O.F., Vaillant, Y., Marić, J., 2023. Is digital transformation equally attractive to all manufacturers? Contextualizing the operational and customer benefits of smart manufacturing. Int. J. Phys. Distrib. Logist. Manag. 53 (4), 489–511. https://doi.org/10.1108/IJPDLM-12-2021-0538/FULL/PDF.

Opazo-Basáez, M., Bustinza, O.F., Molina, L.M., 2024a. The effect of industrial solution services (ISS) on innovation performance: the moderating role of sustainable development goals (SDGs). J. Clean. Prod., 142265 https://doi.org/10.1016/J.JCLEPRO.2024.142265.

Opazo-Basáez, M., Monroy-Osorio, J.C., Marić, J., 2024b. Evaluating the effect of green technological innovations on organizational and environmental performance: a treble innovation approach. Technovation 129, 102885. https://doi.org/10.1016/j.technovation.2023.102885.

Paiola, M., Schiavone, F., Grandinetti, R., Chen, J., 2021. Digital servitization and sustainability through networking: some evidences from IoT-based business models. J. Bus. Res. 132, 507–516.

Parida, V., Wincent, J., 2019. Why and how to compete through sustainability: a review and outline of trends influencing firm and network-level transformation. Int. Entrep. Manag. J. 15 (1), 1–19. https://doi.org/10.1007/S11365-019-00558-9/FIGURES/2.

Piscicelli, L., 2023. The sustainability impact of a digital circular economy. Curr. Opin. Environ. Sustain. 61, 101251. https://doi.org/10.1016/J.COSUST.2022.101251.

Qi, B., Shen, Y., Xu, T., 2023. An artificial-intelligence-enabled sustainable supply chain model for B2C E-commerce business in the international trade. Technol. Forecast. Soc. Chang. 191, 122491. https://doi.org/10.1016/J.TECHFORE.2023.122491.

Rabetino, R., Kohtamäki, M., Huikkola, T., 2023. Digital service innovation (DSI): a multidisciplinary (re)view of its origins and progress using bibliometric and text mining methods. J. Serv. Manag. https://doi.org/10.1108/JOSM-12-2022-0375, 1757–5818.

Raddats, C., Easingwood, C., 2010. Services growth options for B2B product-centric businesses. Ind. Mark. Manag. 39 (8), 1334–1345. https://doi.org/10.1016/j.indmarman.2010.03.002.

Rawat, R. (2023). Harnessing the Power of IoT and AI for Human Evolution. *April-May 2023*. https://doi.org/10.55529/ijrise.33.58.68.

Rojek, I., Mroziński, A., Kotlarz, P., Macko, M., Mikołajewski, D., 2023. AI-based computational model in sustainable transformation of energy markets. Energies. https://doi.org/10.3390/en16248059.

Rusch, M., Schöggl, J.P., Baumgartner, R.J., 2023. Application of digital technologies for sustainable product management in a circular economy: a review. Bus. Strateg. Environ. 32 (3), 1159–1174.

Sekli, G.F.M., De La Vega, I., 2021. Adoption of big data analytics and its impact on organizational performance in higher education mediated by knowledge management. Journal of Open Innovation: Technology, Market, and Complexity 7 (4), 221.

Shakeel, J., Mardani, A., Chofreh, A.G., Goni, F.A., Klemeš, J.J., 2020. Anatomy of sustainable business model innovation. J. Clean. Prod. 261, 121201. https://doi.org/10.1016/J.JCLEPRO.2020.121201.

Shashi, Centobelli, P., Cerchione, R., Singh, R., 2019. The impact of leanness and innovativeness on environmental and financial performance: insights from Indian SMEs. Int. J. Prod. Econ. 212 (December 2017), 111–124. https://doi.org/10.1016/j.ijpe.2019.02.011.

Sheng, J., Amankwah-Amoah, J., Wang, X., 2017. A multidisciplinary perspective of big data in management research. Int. J. Prod. Econ. 191, 97–112. https://doi.org/10.1016/j.ijpe.2017.06.006.

Sjödin, D., Parida, V., Palmié, M., Wincent, J., 2021. How AI capabilities enable business model innovation: scaling AI through co-evolutionary processes and feedback loops. *J. Bus. Res.* 134, 574–587. https://doi.org/10.1016/J.JBUSRES.2021.05.009.

Sjödin, D., Parida, V., Kohtamäki, M., 2023. Artificial intelligence enabling circular business model innovation in digital servitization: conceptualizing dynamic capabilities, AI capacities, business models and effects. Technol. Forecast. Soc. Chang. 197, 122903. https://doi.org/10.1016/j.techfore.2023.122903.

Stern, N., Valero, A., 2021. Innovation, growth and the transition to net-zero emissions. Res. Policy 50 (9), 104293. https://doi.org/10.1016/J.RESPOL.2021.104293.

Sun, T., Ocko, I.B., Sturcken, E., Hamburg, S.P., 2021. Path to net zero is critical to climate outcome. Sci. Rep. 11 (1), 1–10. https://doi.org/10.1038/s41598-021-01639-y.

Tress, G., Tress, B., Fry, G., 2005. Clarifying integrative research concepts in landscape ecology. Landsc. Ecol. 20 (4), 479–493. https://doi.org/10.1007/s10980-004-3290-4.

Vendrell-Herrero, F., Bustinza, O.F., Opazo-Basaez, M., 2021. Information technologies and product-service innovation: the moderating role of service R&D team structure. J. Bus. Res. 128, 673–687. https://doi.org/10.1016/j.jbusres.2020.01.047.

Verhoef, P.C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi Dong, J., Fabian, N., Haenlein, M., 2021. Digital transformation: a multidisciplinary reflection and research agenda. J. Bus. Res. 122, 889–901. https://doi.org/10.1016/J.JBUSRES.2019.09.022.

Wamba-Taguimdje, S.-L., Fosso Wamba, S., Robert, J., Kamdjoug, K., Emmanuel, C., Wanko, T., 2020. Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects. Bus. Process. Manag. J. 26 (7), 1463–7154. https://doi.org/10.1108/BPMJ-10-2019-0411.

Xiong, Y., Xia, S., Wang, X., 2020. Artificial intelligence and business applications, an introduction. Int. J. Technol. Manag. 84 (1–2), 1–7. https://doi.org/10.1504/IJTM.2020.112615.

Zameer, H., Wang, Y., Saeed, M.R., 2021. Net-zero emission targets and the role of managerial environmental awareness, customer pressure, and regulatory control toward environmental performance. Bus. Strateg. Environ. 30 (8), 4223–4236. https://doi.org/10.1002/BSE.2866.

CHAPTER 7. DISCUSSIONS AND CONCLUSSIONS

Chapter 7: Discussion and Conclusions

7.1 Synthesis of Key Findings from the Articles

The synthesis of findings from the three articles reveals critical insights into the intersection of servitization, digital service innovation (DSI), and sustainability strategies. The first article establishes the historical transition from mass consumption to servitization, outlining the strategic importance of integrating service-oriented approaches into traditional goods-centric business models. This transition emphasizes how servitization reshapes operational frameworks, enabling businesses to enhance efficiency, flexibility, and adaptability in response to evolving consumer demands. The conceptual models proposed in the article highlight how servitization aligns pricing and operational strategies to achieve both economic resilience and incremental contributions to sustainability. By examining the evolution of economic frameworks, the article situates servitization as a foundational element in contemporary business strategies, linking historical practices to current and future challenges in business performance and ecological responsibility.

The second article extends this discourse by investigating the role of DSI and its interaction with artificial intelligence (AI) in optimizing business performance. Through a quantitative analysis, the article identifies DSI as a critical enabler of operational excellence, particularly in its ability to harness by-product and contextual data for strategic decision-making. The mediating role of AI emerges as a focal point, illustrating how AI-driven analytics enhance service delivery, refine customer engagement strategies, and strengthen the decision-making process. The study's findings underscore the importance of aligning technological integration with business objectives, demonstrating that DSI when paired with AI, creates a synergistic effect that amplifies business outcomes and supports sustainability efforts. This empirical evidence positions DSI and AI as complementary elements in the evolution of servitization, bridging traditional service frameworks with digital transformation initiatives.

The third article focuses on applying digital tools in advancing sustainability strategies, particularly in pursuing net-zero emissions. This study introduces a comprehensive framework categorizing digital strategies into digitally enabled and digital-first approaches. Digitally enabled strategies optimize existing systems through

IoT and predictive analytics tools, improving resource efficiency and reducing waste. In contrast, digital-first strategies prioritize the design of inherently sustainable systems, embedding AI and other digital innovations into the core of business operations. The findings highlight the transformative potential of digital technologies in environmental management, emphasizing their ability to enhance precision, transparency, and adaptability in achieving sustainability objectives. These articles provide a holistic understanding of how servitization, DSI, and digital strategies converge to address the dual imperatives of business performance and ecological responsibility.

7.2 Comparative Analysis Across the Articles

While the three articles converge on the critical role of digital transformation in business and sustainability, they differ significantly in their focus and methodological approaches. The first article adopts a conceptual and historical perspective, offering a theoretical exploration of Servitization and its strategic implications. This approach is valuable in understanding the foundational elements of Servitization and its evolution but is less focused on operationalizing these concepts in contemporary contexts. In contrast, the second article employs a quantitative methodology, using structural equation modelling to examine the interplay between DSI, AI, and business performance. This empirical approach provides actionable insights into how digital tools mediate and enhance the effectiveness of service-oriented strategies. By operationalizing key variables such as customer feedback and usage data, the study bridges the theoretical underpinnings of Servitization with practical applications in modern business environments.

The third article complements these perspectives by focusing on the broader implications of digital strategies for sustainability. Employing a mixed-methods approach, this study integrates quantitative data with qualitative insights to explore the practical implementation of digital tools in achieving net-zero objectives. By distinguishing between digitally enabled and digital-first strategies, the article provides a nuanced framework for understanding the diverse pathways through which firms adopt and benefit from digital innovations. Unlike the first and second articles, which concentrate on business performance and operational efficiency, this study prioritizes environmental management and sustainability outcomes. These differences highlight the complementary nature of the three articles, as they collectively address the historical, operational, and ecological dimensions of Servitization and digital transformation. Together, they comprehensively view how businesses can integrate Servitization and digital strategies to achieve economic and environmental goals.

Moreover, all the three articles converge on the critical role of digital transformation in business and sustainability, they differ significantly in their focus, methodological approaches, and core contributions. The first article emphasizes the historical evolution of Servitization and its role in transitioning business models from goods-centric to service-oriented frameworks. The article outlines how operational strategies—such as aligning pricing with service offerings—enhance business adaptability and incremental sustainability by inducting Servitization within its historical and strategic context. However, it is less focused on operationalizing these concepts in modern contexts, providing instead a foundational perspective that connects Servitization's origins with its potential future applications. In contrast, the second article explores the transformative role of digital service innovation (DSI) and artificial intelligence (AI) in enhancing service ecosystems and business performance. Employing a quantitative methodology highlights how AI mediates DSI's impact, operationalizing key variables such as customer feedback and usage data to demonstrate actionable pathways for improving decision-making and customer engagement. This article bridges theoretical foundations with practical insights, showcasing AI as a pivotal enabler of digital transformation. The third article complements these perspectives by examining the implications of digital tools, such as IoT and AI, in achieving net-zero objectives. It adopts a mixed-methods approach to propose a nuanced framework that categorizes sustainability strategies into digitally enabled approaches, which optimize existing processes, and digital-first strategies, which embed sustainability principles from the outset. Unlike the first and second articles, which focus primarily on business performance and operational efficiency, this article prioritizes environmental management, offering actionable insights into emissions reduction and resource optimization. These differences underscore the complementary nature of the three studies, each addressing historical, operational, and ecological dimensions of Servitization and digital transformation. Core contributions include Servitization's historical and operational strategies (Paper 1), AI's transformative role in enhancing digital services (Paper 2), and IoT-driven approaches within digital sustainability frameworks (Paper 3), with key sub-topics enriching each area. Collectively, these contributions align around a central implication: the convergence of future tech-enabled strategies, emphasizing sustainability, efficiency, and adaptability as key trends shaping business and environmental outcomes.

In summary Servitization and service innovation are interconnected concepts that collectively shape contemporary business strategies by integrating product-service systems and technological advancements. Servitization emphasizes the transition from traditional product-based models to those combining goods and services, offering comprehensive solutions tailored to consumer needs. This transition influences theoretical contributions by reframing how value is conceptualized and delivered in academic and practical settings. Empirically, Servitization supports data-driven analyses of its impact on operational efficiency, customer retention, and long-term business sustainability. Managerially, it informs strategies for resource allocation, supply chain integration, and customer-centric decision-making.

Additionally, Servitization contributes to future-oriented frameworks, particularly in fostering sustainability by promoting circular economy principles and extending product lifecycles. In parallel, service innovation complements this process by developing new or improved service delivery mechanisms underpinned by digital transformation. Theoretically, it advances the understanding of how emerging technologies such as artificial intelligence (AI) and the Internet of Things (IoT) redefine service ecosystems. Empirical analyses of service innovation highlight its role in enhancing customer engagement, improving operational scalability, and optimizing predictive models. Managerially, service innovation aids businesses in navigating digital disruption by leveraging technologies to improve service delivery and align offerings with evolving market demands.

Furthermore, its contributions to sustainability are evident in its ability to enable resource-efficient services and support adaptive, environmentally responsible solutions. The interplay between Servitization and service innovation is particularly pronounced in their shared emphasis on fostering sustainability and improving customer satisfaction through integrated service systems. For instance, Servitization often relies on service innovation to incorporate advanced technologies, while service innovation frequently utilizes the frameworks that Servitization has established to operationalize new models effectively. Both concepts influence and are influenced by broader trends in digital transformation, creating a dynamic relationship that shapes theoretical discourse, empirical research, and managerial practices. Together, they form a comprehensive paradigm that addresses contemporary challenges in efficiency, sustainability, and customer-centricity across industries. Figure 1 represents the connections between publications in the order of conclusions and relevant topics around the community of Servitization.

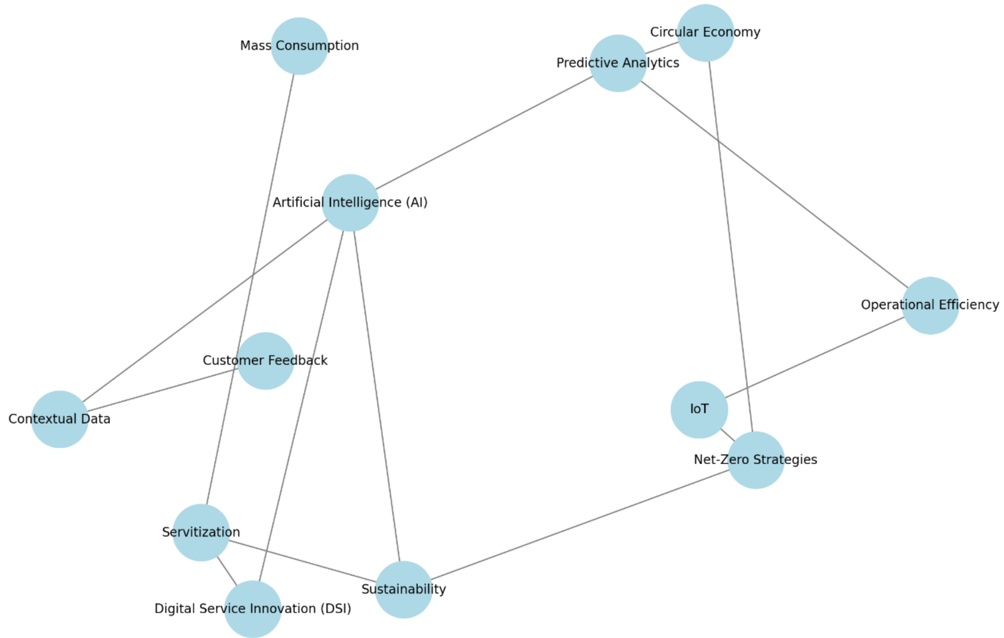

Figure 1: Conceptual network graph with correlation of concepts in papers conclusions.

<u>7.3 Reflection on Theoretical and Practical Implications of the Research</u>

The findings from the three articles offer significant theoretical and practical implications, contributing to the academic understanding of servitization, DSI, and sustainability while providing actionable insights for practitioners. Theoretically, the research enriches the servitization literature by linking it with digital transformation frameworks and sustainability paradigms. Integrating AI and IoT within servitization and DSI strategies expands the applicability of theories such as Organizational Information Processing Theory (OIPT), offering new perspectives on aligning information flows with strategic objectives. By demonstrating the mediating role of AI in enhancing business performance, the studies highlight how digital tools facilitate value creation, optimize decision-making, and enable the development of adaptive service models. These theoretical advancements underline the evolving nature of servitization and its relevance in addressing contemporary challenges in business and sustainability.

From a practical standpoint, the research provides valuable insights for firms seeking to integrate digital and service-oriented strategies into their operations. Identifying digitally enabled and digital-first approaches offers a strategic framework for businesses to navigate their sustainability journeys. Firms can adopt digitally enabled strategies to optimize existing systems, achieving immediate efficiency and resource conservation gains. Alternatively, digital-first strategies enable the development of innovative solutions designed from inception to meet sustainability objectives, offering long-term benefits in terms of environmental impact and market competitiveness. Case studies of manufacturing firms employing predictive maintenance, energy optimization, and emissions tracking technologies illustrate the practical applications of these strategies. By leveraging digital tools to align business practices with sustainability goals, firms can enhance their operational resilience, comply with regulatory requirements, and address societal expectations for responsible corporate behaviour. The findings from the three articles offer significant theoretical and practical implications, contributing to the academic understanding of servitization, DSI, and sustainability while providing actionable insights for practitioners. Theoretically, the research enriches the servitization literature by linking it with digital transformation frameworks and sustainability paradigms. Integrating AI and IoT within servitization and DSI strategies expands the applicability of theories such as Organizational Information Processing Theory (OIPT), offering new perspectives on aligning information flows with strategic objectives. By demonstrating the mediating role of AI in enhancing business performance, the studies highlight how digital tools facilitate value creation, optimize decision-making, and enable the development of adaptive service models. These theoretical advancements underline the evolving nature of servitization and its relevance in addressing contemporary challenges in business and sustainability.

Finally, from a practical standpoint, the research provides valuable insights for firms seeking to integrate digital and service-oriented strategies into their operations. Identifying digitally enabled and digital-first approaches offers a strategic framework for businesses to navigate their sustainability journeys. Firms can adopt digitally enabled strategies to optimize existing systems, achieving immediate efficiency and resource conservation gains. Alternatively, digital-first strategies enable the development of innovative solutions designed from inception to meet sustainability objectives, offering long-term benefits in terms of environmental impact and market competitiveness. Case studies of manufacturing firms employing predictive maintenance, energy optimization, and emissions tracking technologies illustrate the practical applications of these strategies. By leveraging digital tools to align business practices with sustainability goals, firms can enhance their operational resilience, comply with regulatory requirements, and address societal expectations for responsible corporate behavior.

7.4 Suggestions for Future Research Directions

Despite the contributions of the three articles, several areas remain underexplored, presenting opportunities for future research. Longitudinal studies are needed to assess the long-term impacts of servitization and digital transformation strategies on business performance and sustainability outcomes. Research could provide deeper insights into the dynamic interplay between digital tools, service innovation, and environmental objectives, offering evidence-based recommendations for firms navigating these transitions. Further investigation into the ethical and governance challenges associated with AI and IoT is also essential. Issues such as data privacy, algorithmic biases, and equitable access to digital technologies warrant closer examination, particularly in their application in sustainability strategies.

Expanding the scope of analysis to include diverse industries and geographic regions would also enhance the generalisability of the findings. While the articles focus predominantly on Spanish manufacturing firms, extending this research to other sectors and regions could provide a more comprehensive understanding of how servitization and digital strategies influence global sustainability efforts. Finally, integrating advanced machine learning models into future research could facilitate the simulation and prediction of various sustainability scenarios, enabling firms to make informed decisions about adopting and implementing digital tools. Such advancements would contribute to developing robust decision-making frameworks, ensuring businesses remain agile and responsive in the face of evolving environmental and market challenges. Table 2 summarize the contributions and implications of the complete research

Dimension	Article 1: From Mass Consumption to Servitization	Article 2: Assessing the Impact of DSI on Business Performance	Article 3: Charting the Digital Route to Net-Zero
Conceptual Contribution	Highlights the historical evolution of servitization and its role in transitioning from product-centric to service-oriented models.	Establishes the mediating role of AI in maximizing the impact of DSI on business performance.	Proposes a framework for digitally enabled and digital-first strategies to support sustainability.
Theoretical Contribution	Develops frameworks for aligning operational strategies with servitization principles, focusing on cost efficiency and adaptability.	Expands OIPT by linking AI, DSI, and performance metrics in service ecosystems.	Connects digital tools (IoT, AI) with sustainability strategies, focusing on net-zero goals.
Empirical Contribution	Demonstrates the importance of service-oriented strategies for addressing contemporary market demands and sustainability needs.	Provides quantitative evidence of the relationship between DSI, AI, and business outcomes.	Identifies practical applications of digital tools in resource optimization and emissions management.
Managerial Contribution	Offers insights into how servitization can improve operational flexibility and create incremental sustainability benefits.	Recommends integrating DSI and AI to enhance decision-making, customer engagement, and efficiency.	Guides industries in adopting digital-first approaches for long-term sustainability and innovation.
Future Implications	Calls for further integration of servitization and technology to address sustainability and performance challenges holistically.	Suggests the need for further exploration of AI's role in driving advanced service ecosystems.	Emphasizes the importance of digital innovation in achieving systemic sustainability transformation.

Table 2: Contributions from the three papers

8. References.

Baines, T., & Lightfoot, H. (2013). *Made to Serve: How Manufacturers can Compete Through Servitization and Product Service Systems* (1st ed.). John Wiley & Sons, Ltd Registered.

B.Holbrook, M., Value, C., & B.Holbrook, M. (2002). Consumer Value. *Consumer Value - A Framework for Analysis and Research*, *2*, 197. https://doi.org/10.4324/9780203010679

Brax, S. A. (2005). A manufacturer becoming service provider - Challenges and a paradox. *Managing Service Quality*, *15*(2), 142–155. https://doi.org/10.1108/09604520510585334

Bustinza, O. F., Vendrell-Herrero, F., Gomes, E., Lafuente, E., Opazo-Basaez, M., Rabetino, R., & Vaillant, Y. (2018). Product-service innovation and performance: unveiling the complexities. *International Journal of Business Environment*, *10*(2), 95–111. https://doi.org/10.1504/IJBE.2018.095819

Calabretta, G., De Lille, C., Beck, C., & Tanghe, J. (2016, May). Service Design for Effective Servitization and New Service Implementation. In *Service design geographies. Proceedings of the ServDes. 2016 conference* (Vol. 125, pp. 91-104).

Cenamor, J., Rönnberg Sjödin, D., & Parida, V. (2017). Adopting a platform approach in servitization: Leveraging the value of digitalization. *International Journal of Production Economics*, *192*(November 2015), 54–65. https://doi.org/10.1016/j.ijpe.2016.12.033

Coreynen, W., Matthyssens, P., Struyf, B., & Vanhaverbeke, W. (2023). Spiraling between learning and alignment toward digital service innovation. *Journal of Service Management*. https://doi.org/10.1108/JOSM-12-2022-0400

Corner, P. D., Kinicki, A. J., & Keats, B. W. (1994). Integrating Organizational and Individual Information Processing Perspectives on Choice. *Organization Science*, *5*(3), 294–308. https://doi.org/10.1287/orsc.5.3.294

Dubey, R., Gunasekaran, A., Childe, S. J., Bryde, D. J., Giannakis, M., Foropon, C., Roubaud, D., & Hazen, B. T. (2020). Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations. *International Journal of Production Economics*, *226*, 107599. https://doi.org/10.1016/J.IJPE.2019.107599

Edwards, M. G. (2021). The growth paradox, sustainable development, and business strategy. *Business Strategy and the Environment*, *30*(7), 3079–3094. https://doi.org/10.1002/BSE.2790

Falcke, L., Zobel, A.-K., Comello, S. D., Gregory-Smith, D., Cooper, C. L., & Bauer, F. (2024). How firms realign to tackle the grand challenge of climate change: An innovation ecosystems perspective. *Journal of Product Innovation Management*, *41*(2), 403–427. https://doi.org/10.1111/JPIM.12687

Falcke, L., Zobel, A.-K., Yoo, Y., & Tucci, C. (2024). Digital Sustainability Strategies: Digitally Enabled and Digital-First Innovation for Net Zero. *Https://Doi.Org/10.5465/Amp.2023.0169*. https://doi.org/10.5465/AMP.2023.0169

Favoretto, C., Mendes, G. H. S., Oliveira, M. G., Cauchick-Miguel, P. A., & Coreynen, W. (2022). From servitization to digital servitization: How digitalization transforms companies' transition towards services. *Industrial Marketing Management*, *102*, 104–121. https://doi.org/10.1016/j.indmarman.2022.01.003

Garcia Martin, P. C., Schroeder, A., Ziaee Bigdeli, A., Carolina, P., Martin, G., Schroeder, A., Ziaee Bigdeli, A., Garcia Martin, P. C., Schroeder, A., Ziaee Bigdeli, A., Carolina, P., Martin, G., Schroeder, A., & Ziaee Bigdeli, A. (2019). The value architecture of servitization: Expanding the research scope. *Journal of Business Research*, *104*, 438–449. https://doi.org/10.1016/j.jbusres.2019.04.010

Gebauer, H., Paiola, M., Saccani, N., & Rapaccini, M. (2021). Digital servitization: Crossing the perspectives of digitization and servitization. *Industrial Marketing Management*, *93*, 382–388. https://doi.org/10.1016/j.indmarman.2020.05.011

Häikiö, J., & Koivumäki, T. (2016). Exploring Digital Service Innovation Process Through Value Creation. *Journal of Innovation Management*, *4*(2), 96–124. https://doi.org/10.24840/2183-0606_004.002_0006

Hallowell, R. (1996). The relationships of customer satisfaction, customer loyalty, and profitability: An empirical study. *International Journal of Service Industry Management*, *7*(4), 27–42. https://doi.org/10.1108/09564239610129931

Haußmann, C., Dwivedi, Y. K., Venkitachalam, K., & Williams, M. D. (2012). *A Summary and Review of Galbraith's Organizational Information Processing Theory*. 71–93. https://doi.org/10.1007/978-1-4419-9707-4_5

Huang, M. H., & Rust, R. T. (2018). Artificial Intelligence in Service. *Journal of Service Research*, *21*(2), 155–172. https://doi.org/10.1177/1094670517752459/ASSET/IMAGES/LARGE/10.1177_1094670517752459-FIG4.JPEG

Huikkola, T., Rabetino, R., Kohtamäki, M., & Gebauer, H. (2020). Firm boundaries in servitization: Interplay and repositioning practices. *Industrial Marketing Management*, *90*, 90–105. https://doi.org/10.1016/j.indmarman.2020.06.014

Kamp, B., Zabala, K., & Zubiaurre, A. (2023). How can machine tool builders capture value from smart services? Avoiding the service and digitalization paradox. *Journal of Business & Industrial Marketing*, *38*(2), 303–316. https://doi.org/10.1108/JBIM-12-2021-0588

Keiningham, T. L., Cooil, B., Aksoy, L., Andreassen, T. W., & Weiner, J. (2007). The value of different customer satisfaction and loyalty metrics in predicting customer retention, recommendation, and share-of-wallet. *Managing Service Quality: An International Journal*, *17*(4), 361–384. https://doi.org/10.1108/09604520710760526

Khanra, S., Dhir, A., Parida, V., & Kohtamäki, M. (2021). Servitization research: A review and bibliometric analysis of past achievements and future promises. *Journal of Business Research*, *131*, 151–166. https://doi.org/10.1016/j.jbusres.2021.03.056

Kohtamäki, M., Bhandari, K. R., Rabetino, R., & Ranta, M. (2024). Sustainable servitization in product manufacturing companies: The relationship between firm's sustainability emphasis and profitability and the moderating role of servitization. *Technovation*, *129*, 102907. https://doi.org/10.1016/J.TECHNOVATION.2023.102907

Kohtamäki, M., Parida, V., Patel, P. C., & Gebauer, H. (2020). The relationship between digitalization and servitization: The role of servitization in capturing the financial potential of digitalization. *Technological Forecasting and Social Change*, *151*, 119804. https://doi.org/10.1016/j.techfore.2019.119804

Kohtamäki, M., Rabetino, R., & Einola, S. (2018). Paradoxes in Servitization. In *Practices and Tools for Servitization* (pp. 185–199). Springer International Publishing. https://doi.org/10.1007/978-3-319-76517-4_10

Kohtamäki, M., Rabetino, R., Parida, V., Sjödin, D., & Henneberg, S. (2022). Managing digital servitization toward smart solutions: Framing the connections between technologies, business models, and ecosystems. *Industrial Marketing Management*, *105*, 253–267. https://doi.org/10.1016/J.INDMARMAN.2022.06.010

Kowalczyk, M., & Buxmann, P. (2014). Big Data and Information Processing in Organizational Decision Processes. *Business & Information Systems Engineering*, *6*(5), 267–278. https://doi.org/10.1007/s12599-014-0341-5

Kowalkowski, C., Wirtz, J., & Ehret, M. (2023). Digital service innovation in B2B markets. *Journal of Service Management*. https://doi.org/10.1108/JOSM-12-2022-0403

Lusch, R. F., & Vargo, S. L. (2014). *The Service-Dominant Logic of Marketing* (Issue January). Routledge. https://doi.org/10.4324/9781315699035

Lusch, R. F., Vargo, S. L., & Malter, A. J. (2006). Marketing as Service-Exchange: *Organizational Dynamics*, *35*(3), 264–278. https://doi.org/10.1016/j.orgdyn.2006.05.008

Manser Payne, E. H., Dahl, A. J., & Peltier, J. (2021). Digital servitization value co-creation framework for AI services: a research agenda for digital transformation in financial service ecosystems. *Journal of Research in Interactive Marketing*, *15*(2), 200–222. https://doi.org/10.1108/JRIM-12-2020-0252

Matyushok, V., Krasavina, V., Berezin, A., & García, J. S. (2021). The global economy in technological transformation conditions: A review of modern trends. *Economic Research-Ekonomska Istrazivanja*, *34*(1), 1471–1497. https://doi.org/10.1080/1331677X.2020.1844030

Mccollough, M. A., Berry, L. L., & Yadav, M. S. (2000). An Empirical Investigation of Customer Satisfaction after Service Failure and Recovery. *Journal of Service Research*, *3*(2), 121–137. https://doi.org/10.1177/109467050032002

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, *58*(3), 103434. https://doi.org/10.1016/J.IM.2021.103434

Monroy-Osorio, J. C. (2024a). Assessing the impact of digital service innovation (DSI) on business performance: the mediating effect of Artificial Intelligence (AI). *Journal of Enterprise Information Management*. https://doi.org/10.1108/JEIM-02-2024-0095

Monroy-Osorio, J. C. (2024b). Charting the digital route to net-zero: A framework for sustainable industry practices. *Cleaner Logistics and Supply Chain*, *13*, 100191. https://doi.org/10.1016/j.clscn.2024.100191

Monroy-Osorio, J. C., Opazo-Basáez, M., & Vendrell-Herrero, F. (2023). Consumer goods: from mass consumption to servitization. In *Handbook of Industrial Development* (pp. 232–247). Edward Elgar Publishing. https://doi.org/10.4337/9781800379091.00024

Opazo-Basaez, M., Cantín, L. N., & Campos, J. A. (2020). Does distance really matter? Assessing the impact of KIBS proximity on firms' servitization capacity: Evidence from the Basque country. *Investigaciones Regionales*, *2020*(48), 51–68. https://doi.org/10.38191/iirr-jorr.20.020

Opazo-Basáez, M., Monroy-Osorio, J. C., & Marić, J. (2024). Evaluating the effect of green technological innovations on organizational and environmental performance: A treble innovation approach. *Technovation*, *129*, 102885. https://doi.org/10.1016/j.technovation.2023.102885

Opazo-Basáez, M., Vendrell-Herrero, F., & Bustinza, O. F. (2018). Uncovering productivity gains of digital and green servitization: Implications from the automotive industry. *Sustainability (Switzerland)*, *10*(5), 1524. https://doi.org/10.3390/su10051524

Opazo-Basáez, M., Vendrell-Herrero, F., & Bustinza, O. F. (2022). Digital service innovation: a paradigm shift in technological innovation. *Journal of Service Management*, *33*(1), 97–120. https://doi.org/10.1108/JOSM-11-2020-0427

Paiola, M., Schiavone, F., Grandinetti, R., & Chen, J. (2021). Digital servitization and sustainability through networking: Some evidences from IoT-based business models. *Journal of Business Research*, *132*, 507–516. https://doi.org/10.1016/J.JBUSRES.2021.04.047

Park, E., Jang, Y., Kim, J., Jeong, N. J., Bae, K., & del Pobil, A. P. (2019). Determinants of customer satisfaction with airline services: An analysis of customer feedback big data. *Journal of Retailing and Consumer Services*, *51*, 186–190. https://doi.org/10.1016/j.jretconser.2019.06.009

Parker, G., & Van Alstyne, M. (2018). Innovation, openness, and platform control. *Management Science*, *64*(7), 3015–3032. https://doi.org/10.1287/mnsc.2017.2757

Paslauski, C. A., Ayala, N. F., Tortorella, G. L., & Frank, A. G. (2016). The Last Border for Servitization. *Procedia CIRP*, *47*, 394–399. https://doi.org/10.1016/j.procir.2016.03.056

Petrulaitiene, V., Korba, P., Nenonen, S., Jylhä, T., & Junnila, S. (2018). From walls to experience – servitization of workplaces. *Facilities*, *36*(9–10), 525–544. https://doi.org/10.1108/F-07-2017-0072

Piscicelli, L. (2023). The sustainability impact of a digital circular economy. *Current Opinion in Environmental Sustainability*, *61*, 101251. https://doi.org/10.1016/J.COSUST.2022.101251

Rabetino, R., Kohtamäki, M., & Gebauer, H. (2017). Strategy map of servitization. *International Journal of Production Economics*, *192*(November 2016), 144–156. https://doi.org/10.1016/j.ijpe.2016.11.004

Rabetino, R., Kohtamäki, M., & Huikkola, T. (2023). Digital service innovation (DSI): a multidisciplinary (re)view of its origins and progress using bibliometric and text mining methods. *Journal of Service Management*, 1757–5818. https://doi.org/10.1108/JOSM-12-2022-0375

Raddats, C., Kowalkowski, C., Benedettini, O., Burton, J., & Gebauer, H. (2019). Servitization: A contemporary thematic review of four major research streams. *Industrial Marketing Management*, *83*(October 2018), 207–223. https://doi.org/10.1016/j.indmarman.2019.03.015

Ranjan, J., & Foropon, C. (2021). Big Data Analytics in Building the Competitive Intelligence of Organizations. *International Journal of Information Management*, *56*, 102231. https://doi.org/10.1016/J.IJINFOMGT.2020.102231

Savva, M., Kong, N., Chhajta, A., Li, F. F., Agrawala, M., & Heer, J. (2011). ReVision: Automated classification, analysis and redesign of chart images. *UIST'11 - Proceedings of the 24th Annual ACM Symposium on User Interface Software and Technology*, 393–402. https://doi.org/10.1145/2047196.2047247

Shankar, V. (2018). How Artificial Intelligence (AI) is Reshaping Retailing. *Journal of Retailing*, *94*(4), vi–xi. https://doi.org/10.1016/S0022-4359(18)30076-9

Sjödin, D., Parida, V., Kohtamäki, M., & Wincent, J. (2020). An agile co-creation process for digital servitization: A micro-service innovation approach. *Journal of Business Research*, *112*, 478–491. https://doi.org/10.1016/J.JBUSRES.2020.01.009

Sorescu, A. (2017). Data-Driven Business Model Innovation. *Journal of Product Innovation Management*, *34*(5), 691–696. https://doi.org/10.1111/JPIM.12398

Soto Setzke, D., Riasanow, T., Böhm, M., & Krcmar, H. (2023). Pathways to Digital Service Innovation: The Role of Digital Transformation Strategies in Established Organizations. *Information Systems Frontiers*, *25*(3), 1017–1037. https://doi.org/10.1007/S10796-021-10112-0/TABLES/11

Spring, M., & Araujo, L. (2013). Beyond the service factory: Service innovation in manufacturing supply networks. *Industrial Marketing Management*, *42*(1), 59–70. https://doi.org/10.1016/j.indmarman.2012.11.006

Stern, N., & Valero, A. (2021). Innovation, growth and the transition to net-zero emissions. *Research Policy*, *50*(9), 104293. https://doi.org/10.1016/j.respol.2021.104293

Stole, L. A. (2007). Chapter 34 Price Discrimination and Competition. *Handbook of Industrial Organization*, *3*(06), 2221–2299. https://doi.org/10.1016/S1573-448X(06)03034-2

Valtakoski, A. (2017). Explaining servitization failure and deservitization : A knowledge-based perspective. *Industrial Marketing Management*, *60*, 138–150. https://doi.org/10.1016/j.indmarman.2016.04.009

Van der Byl, C. A., & Slawinski, N. (2015). Embracing Tensions in Corporate Sustainability. *Organization & Environment*, *28*(1), 54–79. https://doi.org/10.1177/1086026615575047

Vargo, S. L., & Akaka, M. A. (2009). Service-Dominant Logic as a Foundation for Service Science: Clarifications. *Service Science*, *1*(1), 32–41. https://doi.org/10.1287/serv.1.1.32

Vargo, S. L., Fehrer, J. A., Wieland, H., & Nariswari, A. (2023). The nature and fundamental elements of digital service innovation. *Journal of Service Management*. https://doi.org/10.1108/JOSM-02-2023-0052

Vargo, S. L., & Lusch, R. F. (2008). Service-dominant logic: continuing the evolution. *Journal of the Academy of Marketing Science*, *36*(1), 1–10. https://doi.org/10.1007/s11747-007-0069-6

Vendrell-Herrero, F., Bustinza, O. F., Parry, G., & Georgantzis, N. (2017). Servitization, digitization and supply chain interdependency. *Industrial Marketing Management*, *60*, 69–81. https://doi.org/10.1016/j.indmarman.2016.06.013

Vendrell-Herrero, F., Parry, G., Opazo-Basaez, M., & Sanchez-Montesinos, F. J. (2018). Does business model experimentation in dynamic contexts enhance value capture? *International Journal of Business Environment*, *10*(1), 14–34. https://doi.org/10.1504/IJBE.2018.093301

Vendrell-Herrero, F., & Wilson, J. R. (2017). Servitization for territorial competitiveness: taxonomy and research agenda. *Competitiveness Review*, *27*(1), 2–11. https://doi.org/10.1108/CR-02-2016-0005

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi Dong, J., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, *122*, 889–901. https://doi.org/10.1016/J.JBUSRES.2019.09.022

Vilkas, M., Bikfalvi, A., Rauleckas, R., & Marcinkevicius, G. (2022). The interplay between product innovation and servitization: the mediating role of digitalization. *Journal of Business & Industrial Marketing*, *37*(11), 2169–2184. https://doi.org/10.1108/JBIM-03-2021-0182

Wasim, M., Ahmed, S., Kalsoom, T., Khan, M. S., & Rafi-Ul-Shan, P. M. (2024). Market orientation and SME performance: Moderating role of IoT and mediating role of creativity. *Journal of Small Business Management*, *62*(2), 938–965. https://doi.org/10.1080/00472778.2022.2100897