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Treble innovation firms: Antecedents, outcomes, and enhancing factors

Ferran Vendrell-Herrero [a,*], Oscar F. Bustinza [b], Marco Opazo-Basaez [c], Emanuel Gomes [d]

[a] Strategy Group, University of Edinburgh Business School, University of Edinburg, 29 Buccleuch Place, Edinburgh, EH8 9JS, United Kingdom
[b] Department of Management I, Faculty of Economics and Business, University of Granada, 18071, Granada, Spain
[c] Deusto Business School, Deusto University, Bilbao, Spain
[d] Nova School of Business and Economics, Universidade Nova, Campus de Carcavelos, 2775-405, Carcavelos, Portugal

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ABSTRACT

Drawing on the interplay between strategic ambidexterity, resource-based view, and digital servitization, we conceptualize how the rise of digitalization and service business models in industrial settings have materialized in a distinctive category of innovation-oriented manufacturing firms, labeled as treble innovation firms. We propose that said firms are characterized by simultaneously developing the three types of technological innovation —process, product, and digital service. We use a random and representative survey of 423 Spanish manufacturing firms to analyze antecedents, outcomes, and enhancers of digital service innovation adoption in firms that already possess process and product innovations (i.e., dual innovation firms). We report several findings. First, treble innovation firms epitomize the new norm (rather than the exception), representing 21.7% of all manufacturing firms. Second, product leadership and open innovation breadth increase the probability that dual innovation firms implement digital service innovation. Third, treble innovation firms achieve considerably greater profit margins than dual innovation firms. Finally, treble innovation firms can enhance said profit advantage by adopting resource retrenchment and value migration practices.

1. Introduction

Manufacturing firms increasingly employ technologies that merge the digital and physical worlds to offer a wider range of technological innovations to create, deliver, and capture greater value from their products throughout their life cycle (Araujo and Spring 2006; Cusumano et al., 2015). These innovations involve not only process and product innovations but also digital service innovations,[1] which add substantial capabilities to the firm to generate value (Barrett et al., 2015; Raddats et al., 2022). This study assesses the performance-enhancing effect of adding digital service innovation in manufacturing firms that already integrate product and process innovations.

Such assessment is of particular importance because previous research on technology management has focused predominantly on examining product (Cooper and Kleinschmidt, 1987), process (Hatch and Mowery, 1998), and/or service (Witell et al., 2016) innovation management separately. Though some studies have investigated the joint effects of product and process innovations (Fritsch and Meschede, 2001; King et al., 2003; Ennen and Richter, 2010) or product and service innovations jointly (Visnjic-Kastalli and Van Looy, 2013; Kindström and Kowalkowski, 2014), no research to date has analyzed the joint effects of product, process, and digital service innovation—what we term *treble innovation*. In today's highly competitive and globalized market, more firms are engaging in treble innovation. The proliferation of this type of firm is of great significance because it strengthens the idea that complementarity exists among different types of technological innovation, a phenomenon that has not been addressed with three types simultaneously. This study thus responds to a call for studies that combine simultaneous adoption of various types of innovation (Toh and Ahuja, 2021).

We draw on the strategic ambidexterity literature (e.g., Raisch and Birkinshaw, 2008; Cao et al., 2009; O'Reilly and Tushman, 2013; Turner

* Corresponding author.
E-mail addresses: fvendrel@ed.ac.uk (F. Vendrell-Herrero), oscarfb@ugr.es (O.F. Bustinza), marco.opazo@deusto.es (M. Opazo-Basaez), emanuel.gomes@novasbe.pt (E. Gomes).

[1] Drawing on Soto Setzke et al. (2021), we conceptualize digital service innovation as the bundling of services and products using digital technologies. In this bundling, the service entity enables real time access to customer data on product usage, and such customer data enables companies to provide recommendations—in the form of services—for improving use of the product. Examples of these services include real time tracking, machine health monitoring, and consultancy-based data analytics, among others.

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et al., 2013) to explain the added value of digital service innovation. We argue that manufacturing industries are entering a new production paradigm led by digital technologies, generating a new form of ambidextrous innovation. We describe a new type of company, the treble innovation firm, defined as a manufacturing firm that combines all three types of technological innovation—process, product, and digital service—simultaneously, thereby deploying new forms of organizational ambidexterity (i.e., exploitative product and process innovation and exploratory service innovation).

Our theoretical argument is as follows. According to industry life-cycle theory, manufacturing firms must invest in product and process innovations (hereafter dual innovation), with firms initially investing in exploratory product innovation and, as competition intensifies, increasing exploratory process innovation to lower production costs (Klepper, 1996). As technology develops, however, product and process innovations progressively become more exploitative (Zhou and Wu, 2010) and firms increasingly implement both forms of technological innovation simultaneously (e.g., Toh and Ahuja, 2021). As a result, most contemporary innovation-intensive manufacturing firms may be unable to rely solely on joint product and process innovations to maintain sustainable competitive advantages. We argue that abnormal positive returns are achieved in modern manufacturing when firms can implement not only product and process innovation (dual innovation) but also digital service innovation—a type of technological innovation based primarily on exploratory development of digitally-enabled customized offerings (Soto Setzke et al., 2021).

We examine not only the effects of treble innovation but also its antecedents and enhancing factors. Our analysis of antecedents draws on the literature on digital servitization (Gebauer et al., 2021) to argue that dual innovation firms with product leadership, open innovation, and/or a larger customer base are more likely to implement digital service innovation. In analyzing enhancing factors, we draw on the resource-based view (RBV) of the firm (e.g., Alexy et al., 2018) to detect groups of treble innovation firms that have had outstanding profitability. These firms exhibit unique capabilities that defuse apparently paradoxical tensions between sharing knowledge and protecting essential resources.

We test the hypotheses on a representative sample of medium-sized Spanish manufacturing firms. The questionnaire administered to 423 firms was designed specifically to answer the questions pursued in this study. The questionnaire data were fused with accounting and financial data from the Bureau van Dijk (BvD) to ensure greater robustness of the results obtained. The empirical design corrects for problems of endogeneity (i.e., confounding variables) by using various matching propensity score and doubly robust estimations.

As a whole, this paper contributes to technological innovation literature in three ways. First, we identify, define, and characterize a new type of innovation-intensive manufacturing firm, the treble innovation firm, which possesses a broader technological innovation portfolio that includes simultaneous product, process, and digital service innovations. Second, the emergence of treble innovation firms is significant because it corroborates the existence of synergetic effects among types of technological innovation, a phenomenon that has mainly been studied using only two types of dual technological innovation—product and process, or product and service—and that is supported by a new model of ambidextrous organization. Third, our proposed new archetype of technological innovation (digital service innovation) responds to a call for more research on digital (Barrett et al., 2015) and technological (e.g., Snyder et al., 2016; Witell et al., 2016) aspects of service innovation, and helps to update holistic models of technological innovation in manufacturing (e.g., Santamaria et al., 2012).

This paper is organized as follows. Section 2 provides the theoretical background for understanding the evolution of different types of technological innovation and the emergence of treble innovation manufacturing firms. Section 3 develops our arguments and proposed empirical hypotheses. Section 4 presents the data and method, and Section 5 analyzes the results of our antecedents, outcomes, and enhancers of treble innovation firms. Section 6 concludes and provides academic and managerial implications.

2. Theoretical framework

2.1. Digital services as a new form of technological innovation

The Oslo Manual describes industrial firms' innovation activity as a multidimensional phenomenon that can be technological and non-technological (OECD, 2018). According to these typologies, technological innovations involve product and process innovations—specifically, firms' introduction of new products or processes. Non-technological innovations, on the other hand, comprise organizational and marketing innovations, such as new packaging, placement, promotion, or pricing criteria, as well as new organizational approaches connected to practices, the workplace, or the firm's external interactions/relationships (Alvarez-Coque et al., 2017).

In manufacturing, technological innovation has concentrated primarily on product and process innovations, in line with the reasoning that both types of innovation hold substantial strategic value for providing enterprises with a competitive advantage (Onufrey and Bergek, 2020). This dual innovation approach has demonstrated a number of benefits, including highly efficient and flexible manufacturing systems, by delivering more variety at reduced costs (Kaplan and Haenlein, 2006), achieving greater customer satisfaction (Arora et al., 2008), responding quickly in fast-changing global markets (Freel, 2005), and differentiating companies in highly competitive markets and segments (Da Silveira et al., 2001). Numerous studies assess the role and effects of dual innovation in an array of industries, including electronics (Lee and Von Tunzelmann, 2005), aerospace (Slayton and Spinardi, 2016), pharmaceuticals (Mazzola et al., 2015), and automotive (Jacobs et al., 2011), with some researchers arguing that dual innovation remains at the forefront of innovation strategies (Bstieler et al., 2018; Cornelius et al., 2021).

As such, and despite the acknowledged importance of servitization as a new strategy for manufacturing organizations (Eloranta and Turunen, 2015; Crozet and Milet, 2017), emphasis has been mostly on product and process innovation, as reflected in the fact that existing OECD typologies do not incorporate service innovation as a conventional innovation category within manufacturing. This approach results in a rather decontextualized definition of service innovation in industrial settings (Kowalkowski and Witell, 2020; Opazo-Basáez et al., 2022). And it is in fact due to this reason that recent developments in service innovation in manufacturing—such as, outcome-based contracts (Batista et al., 2017) and integrated solutions (Aquilante and Vendrell-Herrero, 2021)—are categorized as non-technological innovations, overlooking technological constituents behind most of service offerings described in the servitization literature. Therefore, the objective of this study builds on the synthesis approach[2] by establishing a more nuanced model of technological innovation within manufacturing industries that incorporate a more contextualized view of service innovation in servitized firms.

A new stream of servitization research, known as digital servitization, provides evidence, however, of how service-augmented products

[2] According to Witell et al. (2016) and Carlborg et al. (2014) there are three ways to consider service innovation within the generic innovation literature: assimilation vs demarcation vs synthesis. Assimilation explains service innovation with the lenses of standard innovation models (e.g., Oslo Manual). Demarcation explains service innovation independently of the innovation that occurs in manufacturing settings (e.g., service sector specific literature). Finally, synthesis formulates new theoretical frameworks to integrate the specific characteristics of service innovation to a more holistic model of innovation. Our Treble Innovation approach positions within the synthesis perspective.

can make widespread use of digital technologies to improve distribution, use, and product performance (Barrett et al., 2015; Coreynen et al., 2017; Vendrell-Herrero et al., 2017). According to this stream of research, manufacturing firms use digital services to relaunch their product-service offerings (Gebauer et al., 2021). The underlying effect of this strategy is that digital services become technological innovations in and of themselves because they adopt technological attributes (Rymaszewska et al., 2017; Paschou et al., 2020). From this perspective, the digital service becomes a technological innovation source whose features can be considerably improved, just like those of products or processes (Raddats et al., 2022). Examples of digital services (Tao et al., 2014) are real-time monitoring services (e.g., sensors for remote visualization and analytics), artificial intelligence services (e.g., bots to improve customer engagement), and app-based solution services (e.g., apps to boost user experience). We correspondingly consider digital service innovation as a multifaceted construct that spans the realms of service and technological innovation. As depicted in Fig. 1, service innovation in manufacturing can take technological (e.g., digital service innovation) and non-technological (e.g., outcome-based contracts, integrated solutions) forms, hence digital service innovation should be considered as part of a triad of technological innovations in manufacturing. Considering these three types of technological innovation—product, process, and digital service—we extend the traditional concept of dual innovation (simultaneous deployment of product and process innovation [Hullova et al., 2016]) to treble innovation, an emerging strategy increasingly adopted by manufacturing firms and characterized as an integrated system of innovations in which product, process, and digital service innovations coalesce to enhance business operations and competitiveness. Adoption of digital service innovation provides treble innovators with a major source of competitive advantage, adding capability to use knowledge gleaned from customers, competitors, and firms' own capabilities to create meaningful and innovative service offerings (Sjödin et al., 2020). Adopting digital service innovation involves an important change in the manufacturer's strategic orientation, from transactional or commercial to inter-firm and even inter-industry collaborative relations, and a reconfiguration of manufacturing's traditional competences (i.e., production and product development competences) to align business model component configurations dynamically with customers' needs (Lenka et al., 2018).

2.2. Treble innovation and new forms of ambidextrous technological innovation

Organizations must resolve existing tensions between exploiting existing knowledge and exploring new knowledge as a form of ensuring future competitiveness (Cao et al., 2009; Turner et al., 2013). Business sustainability requires exploiting current competitive advantage but is also fundamental to securing the fruits of future competitive advantage (Raisch and Birkinshaw, 2008). Being able to cope with these tensions is known as organizational ambidexterity (O'Reilly and Tushman, 2013). Technological innovation has played a central role in the organizational ambidexterity literature, where it is widely discussed in light of product and process innovation but does not integrate digital service innovation (e.g., Cho et al., 2020). This section provides a historical overview of technological innovation in manufacturing and the effects of digitally based technologies on ways of conceptualizing organizational ambidexterity. By doing so, we build a new model of ambidextrous innovation in servitized manufacturing firms that lies on the premise of the current state of technology and markets.[3]

Innovation has driven the evolution of manufacturing systems in present-day industry (Duan et al., 2020). The transition to what is now known as contemporary manufacturing has been (and continues to be) characterized by a sequence of five historical stages of innovation with three paradigm shifts, including experience-, machinery-, information-, relationship-, and digitally-based innovations (see Fig. 2). Throughout this progression, each stage of innovation has also been driven (at the same rate) by the types of technological innovation in the firm—that is, process, product, and digital service innovations (Wang et al., 2016). Individually or synergistically, each innovation type has played a role in configuring distinct manufacturing strategies, establishing value creation frameworks and determining strategic orientation in firms (Dibrell et al., 2014).

As Fig. 2 shows, ambidexterity in manufacturing contexts begins to be relevant in the relationship-based historical stage. Holweg (2007) notes that the introduction of lean manufacturing, developed by Toyota, produced a major paradigm shift in manufacturing, to a renewal production system. In this phase, knowledge, processes, products, and ultimately greater value were created and delivered across intra- and inter-firm alliance networks (Shi and Gregory, 1998). At the functional level, this phenomenon was characterized by exploratory innovations in production processes, performed to meet demand for product variation; and by exploitative product-oriented innovation, intended to satisfy multiple customer profiles. Exploratory process innovation, combined with a strong strategy of continuous exploitative product innovation, enabled greater competitiveness in the global market. Ifandoudas and Chapman (2009) suggest, however, that this approach has lost prominence in the 21st century. The ability to improve processes through lean production seems to have reached its limits, undermined by the ever-changing competitive paradigm. In this context, Park et al. (2020) argue that information technologies have redefined the way companies operate, and digitalization has emerged as a new form of ambidextrous innovation.

The manufacturing shift to a digitally-based stage of technological innovation is rapidly re-shaping global manufacturing (Van Riel et al., 2004) toward a paradigm in which highly connected manufacturers gather, transfer, and exploit contextual information in various knowledge forms to optimize production and meet customer demands in real-time. This amalgam of processes is achieved by encapsulating products into a digitally-led physical object that can be delivered to and used by customers (Holmström et al., 2019). In fact, Porter and Heppelmann (2014) suggest that manufacturers have begun to adopt advanced digital technologies (such as big data, cloud computing, artificial intelligence, and sensors), moving rapidly toward the model of connected and digitally augmented enterprises.

This process of digital transformation has brought tensions and opportunities to the firm's innovative function (Lanzolla et al., 2021). In this regard, the dynamism of digital technologies makes them more complex and less profitable to imitate than more established innovations, including new products and processes (Giachetti and Pira, 2022). This implies that the path to differentiation is more aligned to digitization (exploration strategy), and that product and process innovations become of exploitative nature. In addition, digital technologies have come hand in hand with a growing importance of services in manufacturing (Visnjic-Kastalli and Van Looy, 2013). Wang et al. (2021) have shown that advanced servitization (based largely on digital service innovation) tend to make product innovations more incremental (less radical) to extract more value from installed product portfolio.

Altogether, digital service innovation in this context requires a more exploratory approach—facilitated by digitally-based technological advances that enable manufacturers to fuse product and service offerings (Bustinza et al., 2020). This approach resulted in a new manufacturing archetype, treble innovation, an emerging type of firm that uses its technological resources to optimize processes, products, and digital services simultaneously to empower manufacturing as a whole. Treble innovation firms benefit from a pioneering confluence of innovations in which they incorporate not only exploitative innovations in product and

[3] The historical model depicted in Fig. 2 already identifies three paradigm shifts. Upcoming models of manufacturing will need to take into consideration how the digitally-based paradigm shift has influenced ambidexterity and technological innovation frameworks.

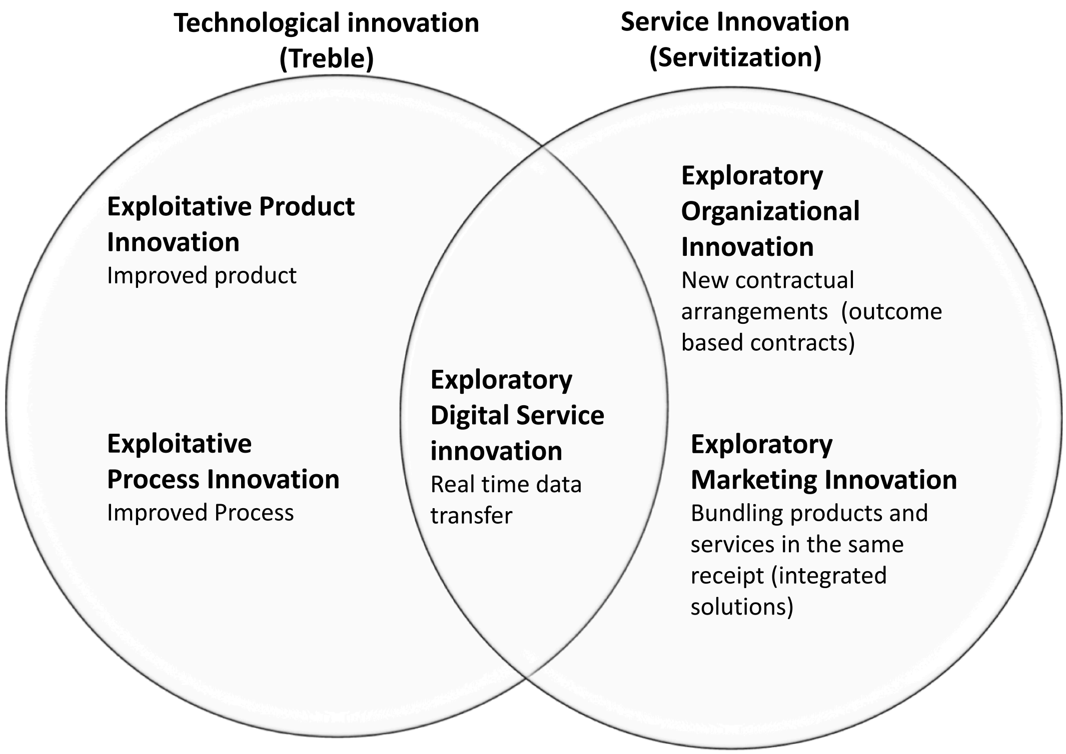

Fig. 1. The role of digital service innovation.
Digital service innovation depicts the intersection between technological innovation and service innovation. This framework describes a digitally-based paradigm shift in which explorative innovations tend to relate to service and digital business models, whilst exploitative innovations tend to relate (though not exclusively) to product and process improvements. Further described in next section.

		Paradigm shift		Paradigm shift	Paradigm shift
Innovation stage	Experience-based	Machinery-based	Information-based	Relationship-based	Digitally-based
Production paradigm	Craft production	Mass production	Mass production	Lean production	Servitization
	Manual production of customised goods	Assembly line and the large scale production of standardised goods	Large scale & scope of differentiated goods	Large scale & scope of differentiated goods Lean production processes	Integrated product-service innovation
Resource-Knowledge acquisition-transfer mechanisms	knowledge and experience individually transmitted from master to apprentice or through professional guilds	knowledge and experience formally codified and collectively transmitted within the company	knowledge and information formally codified and transmitted across the various company's brands	knowledge and information transmitted across the the various company's brands and alliance network	knowledge and technology shared across industries through open innovation and ecosystems Industry fusion
Type of innovation	Exploitative *product* innovation	Exploratory *process* innovation	Exploratory *product* innovation	Exploratory *process* & Exploitative *product* innovation	Exploitative *process* & *product* innovation & Exploratory *digital service* innovation
Representative firm	Artisans	Ford – ´Fordism´	GM	Toyota – ´Toyotism´	Manufacturers-KIBS

Fig. 2. The evolution of ambidextrous technological innovation.

process (i.e., a dual innovation approach) but also exploratory digital service innovation to build differentiation and sustainable competitive advantage.

3. Hypothesis development

3.1. Antecedents of treble innovation

The move toward digital service innovation in manufacturing brings new challenges, requiring revision to the fundamental tenets of value creation (Spring and Araujo 2017), all of which accentuate the significance of designing the right organizational structure, as well as business functions (Gebauer et al., 2021) and consistent selection of business strategies that overcome digital service innovation complexities (Barrett et al., 2015). We thus argue that viewing digital service innovation as the distinctive technological innovation component for transitioning from a dual into a treble innovation firm enables digital service innovation in manufacturing firms. The transition is achieved through market-oriented business strategies such as product leadership, open innovation, and a large customer base, which in turn facilitate digital service innovation adoption, stimulating the transition to treble innovation. To develop this argument, we drew on the digital servitization literature as a general theoretical perspective for examining adoption of digital service innovation in manufacturing contexts (Coreynen et al., 2017). Digital servitization suggests that service infusion in manufacturing firms originated as a transformational process from selling products to selling integrated combinations of products, basic services (e.g., maintenance), knowledge-intensive services (e.g., consulting), and digitally-enabled services (e.g., sensors, artificial intelligence, and app-based solutions) to create additional customer value (Paschou et al., 2020). Within this literature, research describes antecedents, factors, critical issues, and prerequisites to achieving servitization (Baines et al., 2017; Vendrell-Herrero et al., 2017). Since digital servitization is a progressive process that fosters continued service improvement and thus innovation in service (Visnjic-Kastalli and Van Looy, 2013), we use the digital servitization framework to analyze factors that increase the likelihood of adopting digital service innovation in dual innovation firms.

Firms that are product leaders are oriented toward continuous product innovation, but they increasingly provide digitally-enabled solutions to improve the perceived value of their offerings (Zeithaml et al., 2014). Hence, product leaders develop products that are complex, technologically innovative, capital intensive, and durable—product features that simultaneously enable service integration to create compelling competitive value propositions (Van Riel et al., 2004). Companies such as Xerox, Caterpillar, and Rolls-Royce, for example, develop new-to-the-market innovative product offerings that generate first mover advantage and industry leadership (Lieberman and Montgomery, 1988). Such strategic, product-driven outcomes have positive effects on competitive positions (e.g., in the targeted market segment) and drive superior customer engagement, which reduces or eliminates competition (i.e., oligopoly or monopoly, respectively [Gebauer, 2008]). Within this strategy, products remain the base and source of profits and revenue, but product leadership and its underlying premium pricing strategies provide the necessary market power to implement service offerings (Jiao et al., 2003) to further increase customer loyalty (Li et al., 2021). In combination, this argument suggests that product leadership enhances dual innovators' probability of exploring digital services and thus transition to treble innovation. Therefore:

H1. Firms with product leadership are more likely to be treble innovators.

Service infusion transformed manufacturing from a closed, individualistic to an open, network-based environment that demands relational and collaborative approaches to innovation (Rabetino et al., 2017). Companies have accordingly opened their internal innovation processes to enrich their knowledge bases during service development through integration of suppliers, customers, and external technological and knowledge sourcing (Almirall and Casadesus-Masanell, 2010; West and Bogers, 2014; Zobel, 2017). By its very nature, open innovation systematically encourages collaboration and knowledge dissemination among customers, suppliers, and competitors (Laursen and Salter, 2006; Tsinopoulos et al., 2018), fostering co-creation among actors (Chesbrough, 2003). Companies such as ABB, Daimler, Siemens, and GE—which have involved customers as co-developers during value propositions (Gassmann et al., 2010)—follow this strategic approach to innovation, enabling firms to better understand customer needs and expectations. Such better understanding provides greater market orientation, enabling firms to respond more quickly to changing market opportunities (Leiponen and Helfat, 2010; Gomes et al., 2020). During new service developments, the exchange and integration of knowledge, technology, and resources from customers and suppliers create a service ecosystem that streamlines service innovation (He et al., 2020; Opresnik and Taisch, 2015). We propose open innovation as a platform that supports development of digital service innovation in dual innovation firms, increasing their probability of becoming treble innovation firms.[4] Thus:

H2. Firms that are more engaged in open innovation are more likely to be treble innovators.

Digital services are highly scalable (Westerlund, 2020). For example, artificial intelligence robots can use cognitive engagement to interact with large number of customers simultaneously without affecting efficiency and quality of service (Davenport and Ronanki, 2018). Similarly, cloud monitoring services can store and exchange vast amounts of information in real time without saturating system capability (Frank et al., 2019). We consider this growth opportunity as especially important in industries with large numbers of customers. Against this backdrop, Business-to-Consumer (B2C) industries perfectly characterize industries with an above-average number of customers (Dotzel and Shankar, 2019; Kreye and van Donk, 2021).

Unlike Business-to-Business (B2B) industries, B2C companies have a larger base of customers with whom they often interact indirectly. In B2C contexts, commercial intermediaries usually sell the product to the end customer, providing no opportunity to develop tailored services. Digital technologies in B2C contexts make it possible to offer standard and customized scalable services to create great business opportunities (van der Burg et al., 2019). Although B2B companies might develop a wider range of service innovations, they are less dependent on the digital/technological component, since they can have close, constant contact with customers (Dotzel and Shankar, 2019). Within such B2B contexts, customers are primarily offered non-technological service innovations, such as consulting, contractual arrangements, or bundling. Although the literature has not categorically determined that B2C companies are more inclined to digital services, it has noticed related behaviors, such as greater interest in digital marketing (Iankova et al., 2019).

Overall, we argue that having a large number of customers enhances the manufacturing firm's incentive to implement digital service innovation, as it facilitates scalability and opens advantageous opportunities for engagement with customers. Thus:

H3. Firms with a larger customer base are more likely to be treble

[4] We cannot completely rule out reverse causality in H2. Although it could be argued that treble innovation firms conduct more open innovation than dual innovation firms, the main aim of this research is to detect confounding variables that enable us to control for endogeneity when testing the relationship between treble innovation and firm performance (i.e., PSM approach). Open innovation can certainly influence both adoption of digital service innovation and firm performance; it is thus a relevant confounding variable, and our framework considers it as an antecedent of treble innovation.

innovators.

3.2. Treble innovation outcomes

As stated, treble innovation firms represent an emerging type of ambidextrous manufacturing firm capable of both exploratory digital service innovations and exploitative innovations regarding products and processes (i.e., dual innovation). Ambidexterity, defined by O'Reilly and Tushman (2004, p. 77) as "an organization's ability to simultaneously pursue both exploitative and exploratory innovations," is a prerequisite for treble innovation. The ability to use knowledge garnered from customers, competitors, and partners to create meaningful and innovative service offerings provides treble innovation firms with a source of sustainable competitive advantage (Raisch and Birkinshaw, 2008; Lenka et al., 2018).

Much research provides evidence of the positive effects of ambidexterity on firm performance (Junni et al., 2013), suggesting that ambidextrous innovation is especially important to firms that operate in fast-changing, high-tech industries (Cao et al., 2009) and knowledge-intensive business service (KIBS) firms that rely on intangible assets and customer relationship management (Vrontis et al., 2017). Junni et al. (2013) argue that this is due to "the elevated level of environmental dynamism in knowledge-intensive service firms and in high-technology industries" (p. 308). We argue that treble innovation firms achieve and maintain a competitive advantage in fast-changing and increasingly uncertain and unpredictable environments by continuously exploiting opportunities for process and product improvements and exploring new digital service opportunities.

By integrating digitally-enabled services into their products and thus offering more complete solutions, treble innovation firms create and capture more value. They differentiate themselves based on exploratory service innovation to explore new service opportunities and create value propositions that excel at problem-solving and facilitate intimate long-term customer relationships (Turner et al., 2013). Although digital service innovation and provision are differentiating elements of treble innovation firms, value creation must also be supported by the ability to meet threshold requirements in operational efficiency and product leadership. Operational efficiency and ultimate value creation must be sustained by continuous exploitative process innovation in terms of decision-making (Vendrell-Herrero et al., 2018), supply chain integration (Bustinza et al., 2020), cost reduction, productivity enhancement (Kaplan and Haenlein, 2006; Baines et al., 2017), and service delivery (Chen et al., 2009). Product leadership and differentiation must be upheld through exploitative product innovation to ensure continuous development of complex, technologically current, capital intensive, durable products that ground integration of services and provision of competitive value propositions (O'Reilly and Tushman, 2013; Rabetino et al., 2017). The combined effect of process, product, and digital service innovation thus offers treble innovation firms a competitive advantage. Greater productivity derived from operational excellence and efficiency (as well as the capability to provide innovative integrated product–service offerings) and supported by product differentiation, leadership, and innovative service differentiation gives treble innovation firms the ability to achieve closer, long-term customer relationships and revenues that ultimately result in greater profitability. Therefore:

H4. Treble innovation firms have greater profitability than do dual innovators.

3.3. Treble innovation enhancers

Developing in-house innovation strategies requires large investments that are inaccessible to most SMEs due to resource limitations (De Massis et al., 2018). Resource limitations are even greater when firms want to develop a broad set of innovations simultaneously. In such circumstances, perceptive resource management might enhance firm profitability by, for example, accessing knowledge externally in lieu of expensive in-house innovation development. We argue that treble innovation firms are better positioned to handle complex knowledge systems than are dual innovation firms, as the former can better resolve tensions between the RBV and open innovation theoretical frameworks. Open innovation suggests that firms surrender control over knowledge resources voluntarily, and the RBV suggests that firms should not share primary resources with external entities (Economides and Katsamakas, 2006).

The RBV explains differences in firm performance. Firms have different sets of resources, and some firms possess rare and valuable resources that drive competitive advantages (Sirmon et al., 2007; Chahal et al., 2020). The RBV indicates that firms should retain close control of such resources to avoid imitation, maintain their rarity, and sustain competitive advantages (Barney, 1991). This idea contradicts the premises of open innovation, which highlights the importance of sharing knowledge and primary resources with external entities (Laursen and Salter, 2006; Leiponen and Helfat, 2010). Despite this apparent dichotomy, Alexy's et al. (2018) model suggests that these two seemingly contradictory views are not mutually exclusive. Their model proposes two conditions under which open innovation systems enhance firm profitability while being simultaneously congruent with the RBV.

As open innovation leads to significant savings in developing internal innovation, it represents a type of cost saving that can take the form of resource retrenchment. By collaborating with partners, suppliers, or customers, firms eventually reduce the production cost of a focal resource (e.g., internal R&D). Resource retrenchment suggests that firms can increase profitability by substituting in-house development (e.g., R&D) for alliances (i.e., sharing knowledge with external entities). Open innovation allows firms to leverage synergies between open and proprietary sources of innovation, generating revenue and profit that are higher than that created from a fully closed innovation system. Through trade-off logic, this approach—termed value migration—enables a firm to surrender control over innovation sources to access strategic innovation networks that raise the value of innovation sources over which the firm still has control.

As argued earlier, firms with greater open innovation intensity are more inclined to become treble innovators. We now build on this argument to add that the effect of treble innovation on firm performance is contingent on engaging in open innovation. More specifically, we argue that treble innovation firms enhance their profit advantage by better managing tensions between protecting and sharing resources. As to resource retrenchment, treble innovation firms' business model enables them to select relevant sources of open innovation, minimizing use of expensive internal knowledge development. Digital service innovation requires continuous interactions with clients that increase firms' understanding of market demands (Vendrell-Herrero et al., 2017). In many cases, inclusion of new services is associated with lower standardization of offerings (Sousa and da Silveira, 2019). Treble innovation firms thus tend to have more customized projects that require firm capabilities to deliver them. For this business model to work, treble innovators collaborate with various external partners that enable such flexibility within the organization (Sjödin et al., 2020). Greater understanding of market demand suggests that treble innovation firms are better positioned to identify projects that will generate greater sales in the near future, requiring a range of firm capabilities that extend beyond what an SME possesses internally. Treble innovation firms could, therefore, obtain greater benefits from developing alliances with external partners. By doing so, treble innovators might be able to innovate with lower internal development of knowledge, reducing production costs (i.e., R&D investment), a change that translates into greater profit margins. Thus:

H5a. The profit advantage of treble innovation firms increases when open innovation is high and internal R&D is low.

As to value migration, treble innovation firms can, for example, share process innovation knowledge to raise the value of a combined product–service offer (Vendrell-Herrero et al., 2018). Process innovation is difficult to imitate because it is inherent in organizational micro-foundations (i.e., workers; Davis and Aggarwal, 2020). It is thus also difficult to share process innovation knowledge fully with potential competitors, as other firms cannot fully imitate all processes in a firm. By cooperating with external entities, however, treble innovation firms may acquire capabilities to deliver processes that underlie digital service innovation. As argued earlier, service-oriented innovation in manufacturing firms is associated with product leadership (Baines et al., 2017). Product firms with market power can engage more easily with clients and establish long-term contracts required to implement digital service innovation (Visnjic-Kastalli and Van Looy, 2013). We argue that treble innovation firms with a dominant market position could sacrifice their processes' competitiveness (i.e., lower productivity) to raise (i.e., migrate) the value of their combined product–service offers. Hence:

H5b. The profit advantage of treble innovation firms increases when process innovation is low and product leadership is high.

The conceptual framework assessed in this study includes six hypotheses in total, shown in Fig. 3.

4. Data and method

4.1. Database

This study assesses contemporary innovation trends in medium-sized Spanish manufacturers. Like other European countries, Spain provides a relevant context in which to examine innovation strategies in medium-sized firms relative to other economies (e.g., United States and China) because Spain's industrial composition includes few large corporations. Private innovation thus occurs largely in medium-sized firms.

We identified the firms' population using the SABI database, a service of BvD (http://sabi.bvdep.com), which provides accounting and financial information on a large set of Spanish firms with good representation of all strata of the business population. We limited the study to a population of Spanish firms with more than 50 employees that work in industries with manufacturing NAICS codes 31 to 33. These codes include industries such as food, beverage, and textile processing (NAICS 31); non-mineral manufacturing, including wood, petroleum, plastics, and chemical processes, and the pharmaceutical industry (NAICS 32); and mineral manufacturing, including construction of hardware, vehicles, machines, turbines, and engines (NAICS 33). We identified a population of 7552 firms (Table 1).

After identifying the population, we sought to produce a statistically representative survey that considers sector composition and population size. Using a Gaussian distribution and confidence level of 95%, we found the minimum target sample size to be 366 firms.[5] Sampling was implemented in collaboration with an industry partner with extensive experience conducting market research. Firms were contacted using computer-assisted telephone interviewing, a method that is cost-effective and can measure the behaviors under study (Couper, 2000). A draft questionnaire was presented to three innovation managers before distribution to ensure that the questions were clear, and an industry partner also helped to restructure the questionnaire. During November and December 2018, companies were contacted by phone until we obtained 438 responses with sector and size composition close to those in the population (bottom of Table 1). Once the survey was completed, it was merged with the SABI database to ensure that monetary values, including revenue and profit during the current and subsequent periods (2018 and 2019), were objective. To assess non-response bias, we compared early and late respondents (i.e., first and last quartile) for size, industry, and performance (Armstrong and Overton, 1977). The t-tests suggested no difference between early and late respondents. We also compared number of employees and return on sales for responding and non-responding firms and found differences between the two groups to be non-significant ($p > 0.1$).

Common method bias (CMB) arises when firms report information from a single source. Such bias can be reduced by merging survey data with objective accounting and financial BvD information, which included a dependent variable (profitability) and two control variables (number of employees and productivity). Due to their complexity, multistage models extend beyond a respondent's cognitive map and reduce CMB (Chang et al., 2010). We thus also reduced CMB by including antecedents and enhancers during analysis.

4.2. Variables

Return on Sales: The dependent variable in this study is firm profitability, operationalized following extant research that evaluates service innovation in product firms (i.e., profit margins; Visnjic-Kastalli and Van Looy, 2013). Our measure of profit margin is return on sales (ROS), calculated by dividing a firm's earnings before interest, taxes, depreciation, and amortization (EBITDA) by annual revenue. Since profitability varies significantly annually, we averaged ROS for the last two years (2018–2019) to estimate a company's normal profits (Carpenter and Sanders, 2002). The advantage of this variable is that it enables direct interpretation of a firm's profit margin. As shown in Table 2, firms' average ROS was 8.3%, firms retained 0.083 cents per euro in the form of profit, and performance was nearly the same in the three sectors analyzed.

Treble Innovation: The innovation dichotomy treble vs. dual is the dependent variable when analyzing the antecedents of treble innovation and the independent variable when analyzing the outcomes of treble innovation. Following the Community Innovation Surveys and World Bank Enterprise Survey methodologies, we asked firms the following question: "During the last three years, did your firm introduce any new or significantly improved product/process/service on the market?" (Cirera and Muzi, 2020). To be classified as a treble innovation firm, a company had to respond positively to having all three innovation types.[6] To be classified as dual, a firm had to respond positively to the questions on process and product innovations and negatively to the question on service innovations. Of the 423 firms that gave complete answers, 92 (22%) were classified as treble innovation firms and 264 (62%) as dual innovation firms (Table 2). The remaining 67 firms were non-innovators or had other innovation profiles. We report descriptive statistics for all complete respondents (423 firms), but the analyses focused only on the sample of firms with treble or dual innovation portfolios (356 firms).

[5] $n = \frac{N*Z^2*p*(1-p)}{((N-1)*e^2)+(Z^2*p*(1-p))}$, where n is the target sample size, N is the population ($N = 7552$), $Z = \pm 1.96$ (confidence level of 95%), e is the margin of error ($e = 5\%$), and p is a realistic estimate of the desired probability ($p = 0.50$).

[6] Questions about product/process/service innovation appeared in different sections of the questionnaire. To ensure that product and process had an exploitative dimension and service an exploratory dimension, we took the following approach. For product and process innovation, we asked firms whether the innovation was an improvement of existing products or processes, or whether the innovated product or process was new to the market. All firms answered that product and process innovation were improvements of existing products and processes. We operationalized exploratory innovation in services by considering their digital dimension. We added the following question for firms that responded affirmatively to having service innovation: "*Is the service innovation embedded in a digital component (i.e. sensors, streaming service, real-time data, etc.)?*" A firm was classified as implementing digital service innovation if it answered both questions affirmatively. To verify the exploratory nature of these innovations, we verified treble innovation using the firm's webpages through Semrush, a marketing analytical software. We determined that the firm provided artificial intelligence services, app-based solution services, and/or real time remote monitoring services (Tao et al., 2014), which at the time of the survey were largely considered as innovations new to the market.

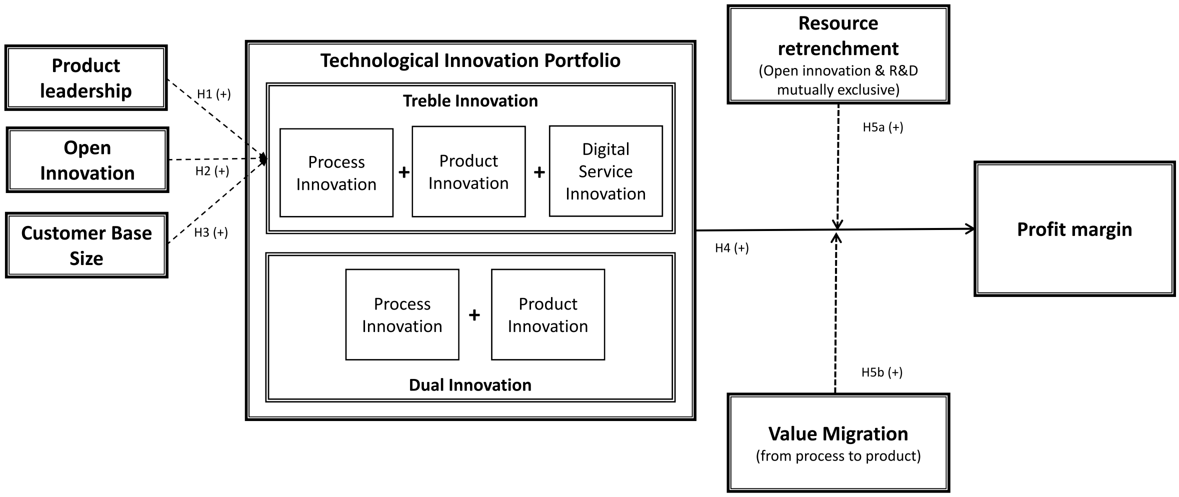

Fig. 3. Conceptual model.

We included antecedents to treble innovation in the model, describing operationalization procedures for *product leadership*, *open innovation*, and *customer base size* in this group of variables.

Product Leadership: As market share and product leadership dynamics are interconnected (e.g., Sutton, 2007), we operationalized product leadership using market share of the main product in the home market (Spain). Based on the market share thresholds proposed by Buzzell et al. (1975), we assigned a value of 1 if the market share of the firm's main product was above 10% of the home market,[7] and zero if it was below. As Table 2 shows, 12.7% of sampled firms were considered as having product leadership, as the market share of their main product in Spain was above 10%.

Open Innovation: We followed Laursen and Salter (2006) in operationalizing breadth of open innovation, creating an index by counting external sources of innovation knowledge—a measure characterized by two substantial differences. The measure Laursen and Salter (2006) use included 16 external information sources (*IS*), but Tsinopoulos et al. (2018) argue that these can be synthesized into three. Two sources refer to existing knowledge within a supply chain—cooperation with suppliers and use of consumer feedback and information—and a third includes other forms of knowledge that extend beyond the supply chain and can be accessed using consulting firms, institutions, or regulatory bodies by contracting the acquisition of external knowledge (i.e., contracts). Whereas Laursen and Salter (2006) assess product innovation, we also assess breadth of knowledge sources used during process innovation. Although Laursen and Salter (2006) calculate breadth in open innovation using 16 sources of external knowledge to create product innovation outcome ($\sum IS$ range between zero and 16), our measure uses three generic sources of external knowledge for two open innovation variables. Our open innovation indices represent the sum of all external information sources divided by three ($\sum IS/3$). The index thus has a minimum of zero (no sources of external innovation) and a maximum of 1 (all possible sources of external innovation). As Table 2 shows, the open process innovation index was 0.306 and the open product innovation index 0.359.

Customer Base Size: B2B firms tend to have a smaller customer base than B2C firms (Dotzel and Shankar, 2019).[8] We therefore asked firms about their main type of customer, providing two response options: end consumer or other companies. We operationalized the variable Customer Base Size using a binary variable that took a value of 1 if a company's primary clients were end consumers (*B2C orientation*) and zero if primary clients were other businesses (*B2B orientation*), a variable that appears in the literature (e.g., Liu et al., 2018; Dotzel and Shankar, 2019). In our sample, 26.7% of firms sold to end consumers.

Control Variables: We controlled for productivity, R&D, and export intensity, which commonly correlate with innovation (Cassiman and Veugelers, 2006). Productivity was measured as *total factor productivity (TFP)*, estimated using Levinsohn and Petrin's (2003) method. All variables required to construct TFP were available in SABI. Sales proxied output, and labor expenses measured labor input. Operating expenses net depreciation, amortization, and labor were used as intermediate inputs, and the book value of fixed assets measured capital. *R&D* was measured as R&D expenditures over sales (Gentry and Shen, 2013). On average, firms spent 5.4% of sales on R&D, but the figure was higher (6.4%) for treble innovation firms.

Export intensity was measured as export sales over total sales (Filatotchev et al., 2008). On average, a firm exported 39% of sales. We also controlled for variables that explain firm heterogeneity, such as *number of workers* and *firm age*. To interpret coefficients more easily, both variables (i.e., size and age) were divided by 100. On average, firms had 236 employees and had operated for 46 years. The model also included dummies for sector and state (i.e., Spanish Autonomous Communities).

4.3. *Empirical design*

We divided the empirical analysis into three stages. The first analyzed factors that increased the likelihood of firms moving from dual to treble innovation. As hypothesized, these factors included product

[7] We also included the 20% threshold in the questionnaire. Only 4.7% of firms reported a market share above 20%. For this threshold, the results are qualitatively the same as those in Table 3. We therefore decided to keep the 10% threshold in the analyses, as having more firms above the threshold facilitates the matching procedure.

[8] We acknowledge that whilst number of customers is one of the most salient characteristics that differentiates B2B and B2C markets, Dotzel and Shankar (2019) propose other important dimensions in which organizational and consumer markets differ. These include customer proximity, service delivery and formality in vendor evaluation. These other dimensions do not invalidate our empirical construct, as they are consistent with our argument that the increase of consumers implicate the impossibility of interaction and evaluation outside a digitalized environment.

Table 1
Sample's technical specifications.

Population	
Universe	Manufacturing firms (NAICS 31, 32, 33)
Source	SABI database (BvD)
Geographical area	Established in Spain, operating in the EU
Population	7552 manufacturing firms
Methodology	Structured questionnaire
Composition of the population	
Smaller firms	NAICS 31 (19.2%)
(fewer than 250 employees)	NAICS 32 (20.4%)
	NAICS 33 (30.3%)
Larger firms	NAICS 31 (7.8%)
(more than 250 employees)	NAICS 32 (9.0%)
	NAICS 33 (13.2%)
Number of employees	225.2
Return on sales	0.078
Sampling procedure	
Type of interview	CATI (Computer-Assisted Telephone Interviewing)
Sample design	Random selection of sampling units
Confidence level	95%
Min. representative sample size	366 manufacturing firms
Sample size	Total answers = 438
	Complete answers = 423
	Relevant to the study (dual and treble) = 356
Response rate	General = 5.79%
	Complete = 5.60%
Sampling error (p = q = 0.50)	±5.13%
Composition of the sample	
Smaller firms	NAICS 31 (24.2%)
(fewer than 250 employees)	NAICS 32 (22.6%)
	NAICS 33 (31.5%)
Larger firms	NAICS 31 (5.9%)
(more than 250 employees)	NAICS 32 (5.7%)
	NAICS 33 (10.0%)
Number of employees	236.4
Return on sales	0.083

leadership (*Pro Lead*), open innovation (*Open Inn*), and customer base size (*Cust base*). We estimated a logistic regression in which treble innovation was the dependent variable. The estimated equation was:

$$Treble_i = \alpha_0 + \alpha_1 * Pro\ Lead_i + \alpha_2 * Open\ Inn_i + \alpha_3 * Cust\ base_i + \Omega_i + \vartheta_s + \varepsilon_i \tag{1}$$

where subscript i denotes the firm; Ω_i is a vector of control variables that includes number of workers, firm age, firm productivity, R&D, and export intensity; ϑ_s indicates industry dummies; and ε_i is the error term. H1, H2, and H3 are supported if parameters α_1, α_2, and α_3, respectively, are larger than zero.

During the second stage, we analyzed the effect of treble innovation on profitability by estimating the linear model:

$$ROS_i = \beta_0 + \beta_1 Treble_i + \Omega_i + \vartheta_s + \vartheta_c + \varepsilon_i \tag{2}$$

where *ROS* is return on sales and *Treble* is the treatment variable. H4 predicts that β_1 will be positive. Ω_i is the same vector of firm characteristics as in Equation (1), ϑ_s are industry dummies, and ϑ_c are state dummies. Controlling for the vector of firm characteristics does not discount the possibility that the relationship between treble innovation and firm profitability is affected by confounding variables and/or reverse causality. We mitigate estimation bias by using treatment models based on propensity score matching (PSM) that reduce bias from observable factors (Lechner, 2002; Uysal, 2015). In experimental data, one can construct a randomized treatment and control group artificially, but this is impossible in the social sciences, where researchers merely observe a firm's decisions. PSM enables construction of a subsample in which control group firms (in our case, dual innovators) are statistically equal to the treatment group in a series of covariates, suggesting that the treatment (in our case, the addition of service innovation in dual innovation manufacturers) differentiates the groups.

Using PSM, we estimated two robust parameters of the treatment effect (β_1 in Equation (2)). The average treatment effect on the firm treated (PSM-ATET) measured the effect of using treble innovation in the subsample treated. The Doubly Robust (PSM-DR) model estimated the treatment and outcome models simultaneously. The treatment effect estimated through DR is more efficient than that estimated through ATET, since the former requires only one of the two models (i.e., treatment and outcome) to estimate the true treatment effect and thus to be specified correctly (Aquilante and Vendrell-Herrero, 2021).

The third stage assessed the role of resource retrenchment and value migration in the relationship between treble innovation and performance. We divided the matched sample into various relevant groups and inspected the difference between the treatment and control groups using *t*-tests. For resource retrenchment, we divided the matched sample into firms with and without R&D, and firms with high and low open innovation. Resource retrenchment was compatible with the finding that treble innovation strategy is superior to dual innovation when open innovation is high and R&D is absent. For value migration, we divided the matched sample into firms with and without product leadership, and firms with high and low firm productivity. These variables proxied quality of product and process innovations, respectively. Value migration was compatible with evidence that the treble innovation performance advantage is highest when quality of product (process) innovation is high (low), indicating that firms can migrate value from process to service by introducing service innovation.

Table 2
Average profile of sampled firms by industry.

		Full Sample	NAICS-31	NAICS-32	NAICS-33
			Food, beverage, and textile	Printing, chemical, and pharmaceutical	Metal, machinery, and hardware
	Observations	423	123	121	179
BvD DATA	# Employees	236.40 (471.39)	218.88 (428.55)	185.47 (170.43)	282.87 (614.17)
	TFP	5.66 (0.75)	5.62 (0.84)	5.75 (0.63)	5.62 (0.76)
	ROS	0.083 (0.113)	0.083 (0.128)	0.081 (0.126)	0.085 (0.090)
SURVEY DATA	Export intensity (%)	39.04 (32.51)	27.52 (28.82)	38.82 (30.95)	47.11 (33.67)
	Firm age	46.80 (34.10)	51.33 (40.28)	42.45 (31.64)	46.63 (30.71)
	R&D investment (%)	5.44 (9.49)	4.95 (7.53)	5.37 (11.33)	5.83 (9.37)
	Product leadership	0.127 (0.334)	0.114 (0.319)	0.141 (0.349)	0.128 (0.335)
	Open innovation (process)	0.306 (0.216)	0.276 (0.247)	0.283 (0.191)	0.342 (0.204)
	Open innovation (product)	0.359 (0.176)	0.314 (0.177)	0.372 (0.178)	0.381 (0.170)
	Customer base size (B2C)	0.267 (0.443)	0.244 (0.431)	0.223 (0.418)	0.312 (0.464)
	Dual innovation	0.624 (0.484)	0.617 (0.487)	0.652 (0.478)	0.608 (0.489)
	Treble innovation	0.217 (0.413)	0.195 (0.397)	0.206 (0.406)	0.240 (0.428)

Note. Standard deviations appear in parentheses. BvD = Bureau van Dijk.

Table 3
Logistic regression: Determinants of treble innovation.

	Model			
	1	2	3	4
Product leadership		0.285***	0.271***	0.279***
		(0.048)	(0.048)	(0.047)
Open innovation (process)			0.383***	0.343***
			(0.101)	(0.100)
Open innovation (product)		0.312**		0.217*
		(0.123)		(0.128)
Customer base size (B2C)		0.093*	0.089*	0.085*
		(0.050)	(0.048)	(0.048)
Export intensity (%)	−0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
# Employees/100	0.006	0.006	0.003	0.004
	(0.005)	(0.006)	(0.007)	(0.006)
R&D investment (%)	0.004	0.003	0.004	0.003
	(0.003)	(0.002)	(0.003)	(0.003)
Age/100	0.089	0.085	0.088	0.087
	(0.066)	(0.059)	(0.063)	(0.061)
TFP	0.052	0.036	0.039	0.036
	(0.036)	(0.034)	(0.034)	(0.034)
Observations	356	356	356	356
Industry FE	yes	yes	yes	yes
McFadden's pseudo-R^2	0.032	0.115	0.136	0.143
AUROC	0.657	0.727	0.755	0.757
Correctly classified (cut-off = 25.8%)				
Sensitivity	58.7%	59.8%	64.1%	64.1%
Specificity	65.5%	73.9%	70.8%	71.6%
Overall	63.7%	70.2%	69.1%	69.7%

Note. Dependent variable is treble innovation firms. Parameters reported are marginal effects.
Robust standard errors appear in parentheses.
*p < 0.1. **p < 0.05. ***p < 0.01.

5. Results

5.1. Stage 1: Treble innovation antecedents (H1, H2, & H3)

We start by estimating a control-variables-only model, Model 1 (Table 3). Although previous studies largely indicate that our control variables (R&D, productivity, exporting, size, etc.) are closely interlinked with innovation outcomes (e.g., Hall et al., 2009; Ganotakis and Love, 2011), our results indicated than none of the control variables explained treble innovation. Moreover, as Model 1's McFadden's pseudo-R^2 highlighted very low fit (0.032), adding a representative set of variables that generally explain innovation outcomes does not improve a constant-only model when differentiating dual from treble innovation firms.[9]

At this point, our goal was to find out whether the model that adds the variables included in our theoretical model substantially improves the explanatory capability of the model. We estimated three additional models. Models 2 and 3 included all independent variables but considered only one measure of open innovation. Model 4 contained all independent variables and both measures of innovation (i.e., process and product). The fit of the full model (Model 4) was considerably better than Model 1, with a McFadden's pseudo-R^2 of 0.143 (log likelihood of −174.39). This level of fitness has been considered acceptable in previous management studies (e.g., Fischer and Leidinger, 2014; Vendrell-Herrero et al., 2022; Wiegmann et al., 2022). Further, Model 4 correctly predicted 69.7% of cases and balanced distribution between specificity (71.6%) and sensitivity (64.1%). The Area under a Receiver-Operating Characteristic (AUROC) was 0.757, above the 0.7 threshold. Overall, the model was considered to have a good fit.

Table 3 reports marginal effects, which measure how much the (conditional) probability of the outcome variable (adopting treble innovation) varies when an independent variable changes. Marginal effects thus provide an economic interpretation (elasticity) of the relationship between independent and dependent variables. According to estimates and assuming all other variables remained constant, firms with product leadership had a greater probability of adopting treble innovation. Firms with a market share larger than 10% were 0.271–0.285 percentage points more likely than firms with a less than 10% market share to adopt treble innovation ($p < 0.01$), a result that supports H1.

In the analysis of open innovation, the results were stronger for the open process innovation index. For Model 4, a 10% increase in open process innovation increased the probability of firms adopting treble innovation by 0.0343 percentage points ($p < 0.01$). Comparison shows that increasing open product innovation by 10% altered the probability of adopting treble innovation by 0.0217 percentage points ($p < 0.10$). That both coefficients were positive supports H2, but treble innovators were more sharply differentiated from dual innovators in sharing process knowledge with external partners, a result relevant to interpreting the migration effect.

Firms with a larger customer base (measured by having a B2C orientation) were slightly more likely to adopt treble innovation than were firms with smaller customer base (B2B orientation). The probability of adopting treble innovation in the full model was 0.085 percentage points larger in B2C firms than in B2B firms, however this result does not reach the commonly accepted threshold of statistical significance ($p = 0.065 > 0.050$), hence we ought to reject H3.

5.2. Stage 2: Treble innovation outcomes (H4)

To calculate an unbiased treatment effect of treble innovation, we constructed a matched subsample using PSM. We started matching by estimating a logit regression (treble vs. dual) and computing scores (Dehejia and Wahba, 2002). The estimates controlled for factors that were significant in Table 3 and the variables introduced during all matching procedures (number of employees and industry dummies). We calculated propensity scores from the results of those estimations. To increase robustness, we constructed four matched subsamples, all based on the nearest-neighbor approach. In all cases, we retained the maximum number of firms in the matched subsample, with the constraint that the difference in propensity score distribution between groups be non-significant at 5%. The Kolmogorov-Smirnov test was used to compare propensity score distributions.

As Table 4 shows, the first matching procedure followed 1:1 PSM with replacement, yielding a matched subsample of 182 firms (91 treble vs. 91 dual). The second followed the same approach but trimmed the sample, imposing common support by dropping 5% of the treatment observations at which the propensity score density of the control observations was lowest, yielding a matched subsample of 176 firms (88 treble vs. 88 dual). As the third procedure used nearest neighbor without replacement, one treatment observation could be paired with more than one control observation, and vice versa, yielding a larger sample of 196 firms by increasing the control sample (91 treble vs. 105 dual). We trimmed to the nearest neighbor without replacement matching, yielding a sample of 191 firms (88 treble vs. 103 dual). In all four cases, we reduced bias (see last column of Table 4).

Table 5 reports ATET and DR treatment estimates for the four matched samples. For ATET, we also report control group effects, which indicate mean outcomes for the control sample (i.e., dual innovators). Values ranged from 0.052 to 0.061, suggesting that dual innovators earned on average 5.2 to 6.1 cents per euro ($p < 0.01$). Treatment

[9] McFadden's pseudo-R^2 calculates how the model considered improves the log likelihood of a constant-only model compared to a model that would have perfect explanatory power (log likelihood of 0). In our case, log likelihood of the constant-only model and Model 1 are −203.42 and −196.87, respectively. Model 1's McFadden's pseudo-R^2 is obtained by calculating 1–196.87/203.42 = 0.032.

Table 4
Propensity score matching (PSM): Reduction bias analysis.

Variables	Difference in means (Before)	*t*-test p-value |diff|>0 (Before)	Difference in means (After)	*t*-test p-value |diff|>0 (After)	Bias reduction (%)
1:1 Nearest Neighbor without replacement (1:1)					
Resulting observations in matched subsample (91 vs. 91)					
Before PSM; KS = 0.401, p = 0.000					
After PSM; KS = 0.154, p = 0.232					
Product leadership	0.228	0.000	0.077	0.119	66.2%
Open innovation (product)	0.043	0.018	−0.018	0.234	141.9%
Open innovation (process)	0.103	0.000	0.000	0.500	100.0%
Customer base size (B2C)	0.113	0.017	0.033	0.318	70.8%
#Employees/100	1.532	0.006	0.640	0.128	58.2%
NAICS-31	−0.027	0.310	−0.065	0.166	−140.7%
NAICS-32	−0.027	0.309	−0.011	0.435	59.3%
NAICS-33	0.054	0.182	0.077	0.149	−42.6%
1:1 Nearest Neighbor without replacement (1:1) – Trimmed at 5%					
Resulting observations in matched subsample (88 vs. 88)					
Before PSM; KS = 0.401, p = 0.000					
After PSM; KS = 0.136, p = 0.387					
Product leadership	0.228	0.000	0.057	0.192	75.0%
Open innovation (product)	0.043	0.018	−0.015	0.276	134.9%
Open innovation (process)	0.103	0.000	0.000	0.500	100.0%
Customer base size (B2C)	0.113	0.017	0.045	0.258	60.2%
#Employees/100	1.532	0.006	0.612	0.146	60.1%
NAICS-31	−0.027	0.310	−0.079	0.126	−192.6%
NAICS-32	−0.027	0.309	−0.011	0.434	59.3%
NAICS-33	0.054	0.182	0.090	0.111	−66.7%
Nearest Neighbor with replacement (NN)					
Resulting observations in matched subsample (91 vs. 105)					
Before PSM; KS = 0.401, p = 0.000					
After PSM; KS = 0.179, p = 0.090					
Product leadership	0.228	0.000	0.106	0.063	53.5%
Open innovation (product)	0.043	0.018	0.022	0.182	48.8%
Open innovation (process)	0.103	0.000	0.034	0.142	67.0%
Customer base size (B2C)	0.113	0.017	0.026	0.348	77.0%
#Employees/100	1.532	0.006	0.210	0.379	86.3%
NAICS-31	−0.027	0.310	−0.050	0.220	−85.2%
NAICS-32	−0.027	0.309	−0.021	0.376	22.2%
NAICS-33	0.054	0.182	0.071	0.159	−31.5%
Nearest Neighbor with replacement (NN) – Trimmed at 5%					
Resulting observations in matched subsample (88 vs. 103)					
Before PSM; KS = 0.401, p = 0.000					
After PSM; KS = 0.174, p = 0.111					
Product leadership	0.228	0.000	0.088	0.074	61.4%
Open innovation (product)	0.043	0.018	0.022	0.176	48.8%
Open innovation (process)	0.103	0.000	0.037	0.115	64.1%
Customer base size (B2C)	0.113	0.017	0.028	0.337	75.2%
#Employees/100	1.532	0.006	0.591	0.144	61.4%
NAICS-31	−0.027	0.310	−0.493	0228	−82.6%
NAICS-32	−0.027	0.309	−0.169	0.400	37.4%
NAICS-33	0.054	0.182	0.661	0.179	−22.4%

Note. Following Dhanorkar (2019), we set the caliper to 0.2 in all cases. KS=Kolmogorov-Smirnov test, which compares equality of distributions for propensity scores before and after matching.

coefficients for ATET suggested additional profit gains by adding digital service innovation in dual innovation firms (4.3–5.1 cents per euro; $p < 0.05$). The ATET model shows that, although dual innovation firms earned on average 5.2 to 6.1 cents per euro, treble innovation firms earned 10.3 to 10.5 cents—a significant difference.

Both the relationship between treble innovation and performance and the effect size became more robust after performing the DR analysis. The DR parameter was nearly the same (0.044–0.049) as the ATET parameter and remained significant ($p < 0.01$ for untrimmed sample, $p < 0.05$ for trimmed sample). According to the DR parameter, treble innovators earned 4.4 to 4.9 cents per euro more than did dual innovators. In combination, the results obtained with the matched sample supported H4 and were not biased, considering observed heterogeneity. Introducing digital service innovation in dual innovation firms thus increases performance.

5.3. Stage 3: Treble innovation enhancers (H5a & H5b)

A previous analysis suggested that the profit margin is 6% for dual innovation firms and 10% for treble innovation firms. The following analysis compares ROS means for various groups of firms to test whether the difference in performance between dual and treble innovation firms increases or decreases (Table 6). We start by testing whether treble innovators enhance their profit margins by using resource retrenchment. We created a 2 × 2 matrix, the vertical dimension of which considers whether a firm invests in R&D. The horizontal dimension considers whether a firm is above or below the midpoint (0.5) in open innovation. To create this variable, we averaged the two measures of open innovation (product and process). Resource retrenchment suggests that intensive use of open innovation can replace R&D investment, enabling a firm to increase profitability by dedicating fewer internal resources to innovation. The profit margin difference between treble and dual innovation firms should thus be accentuated in Quadrant A3, in which firms do not

Table 5
Propensity score matching (PSM): ATET and DR results.

	PSM-ATET		PSM-DR	
	1:1	NN	1:1	NN
Treatment effect (Treble)	0.047**	0.043**	0.048***	0.44***
	(0.021)	(0.020)	(0.004)	(0.004)
Control group effect (Dual)	0.057***	0.061***	–	–
	(0.015)	(0.014)	–	–
Observations	182	196	182	196
R_2	–	–	0.177	0.154
	Sample trimmed at 5%			
Treatment effect (Treble)	0.051**	0.044**	0.049**	0.044**
	(0.022)	(0.021)	(0.009)	(0.005)
Control group effect (Dual)	0.052***	0.061***	–	–
	(0.016)	(0.014)	–	–
Observations	176	191	176	191
R^2	–	–	0.181	0.158
	Control Variables introduced in the model			
Export intensity (%)	Yes	Yes	yes	yes
#Employees/100	Yes	Yes	yes	yes
R&D investment (%)	Yes	Yes	yes	yes
Age/100	Yes	Yes	yes	yes
TFP	Yes	Yes	yes	yes
Industry dummies	Yes	Yes	yes	yes
State dummies	yes	Yes	yes	yes

Note. Dependent variable is return on sales (ROS). P-values shown in parentheses, based on robust standard errors. *$p < 0.1$. **$p < 0.05$. ***$p < 0.01$.

invest in R&D but engage in intensive open innovation.

The results suggest that the treble innovation firms in Quadrant A3 had an average ROS of 0.202, nearly double the average ROS for the entire sample of treble innovators (0.104). Dual innovation firms in Quadrant A3 had an average ROS of 0.056, like the average ROS obtained for the entire sample of dual innovation firms (0.057). The performance difference between dual and treble innovation firms in Quadrant A3 was significant ($p < 0.05$), corroborating the performance-enhancing effect of resource retrenchment in treble innovation firms and supporting H5a.

Panel A also shows that treble innovation firms were more profitable than dual innovation firms in Quadrants A1 and A2. As Quadrant A2 represents the presence of R&D combined with low open innovation, treble firms protected R&D investments by minimizing open innovation. In Quadrant A4, in which R&D was absent and open innovation low, dual innovators outperformed treble innovators, but the difference was non-significant.

Using another 2 × 2 matrix, we tested the role of value migration. The vertical dimension considers whether a firm exhibited product leadership and the horizontal dimension whether a firm was above or below the mean TFP. Value migration suggests that treble innovators use external knowledge to move value from one innovation outcome to another, but it does not address whether firms migrate value from product to process or process to product. Since the results suggested that the differences between treble and dual innovation firms are relevant to open process innovation (Table 3), however, we explored the scenario in which value migrated from process into product. Value migration thus suggests that treble innovators decrease the value of their processes (i.e., lower productivity) to increase the value of their products (i.e., product leadership). Profit advantage should thus appear in Quadrant B2. The results suggest that treble innovation firms in Quadrant B2 had an average ROS of 0.213, more than double the average found for the entire sample of treble innovation firms (0.104). Dual innovation firms in Quadrant B2 had an average ROS of 0.085. The performance difference between dual and treble innovation firms in Quadrant B2 was significant ($p < 0.05$). This result corroborates the performance-enhancing effect of value migration in treble innovation firms, supporting H5b. Although the difference was non-significant, dual innovation firms (0.099) outperformed treble innovation firms (0.083) in Quadrant B1 and had nearly double the average ROS for the entire sample of dual innovators (0.057). Thus, the addition of digital service innovation was insignificant in terms of profit for firms with product leadership, meaning that dual innovation firms had space to compete when they had product leadership.

6. Discussion

6.1. Implications

Although adoption of technological innovations is one of the most critical contemporary topics in manufacturing research, few studies empirically assess adoption of technological innovations simultaneously or their influence on firm performance (Toh and Ahuja, 2021). We address this research gap and expand this body of knowledge by offering insights into adoption of treble technological innovations and their relationships to manufacturing firms' profitability. Grounded in an industry lifecycle perspective comprising progressive innovation stages (Klepper, 1996; Araujo and Spring 2006; Cusumano et al., 2015), this study's principal contribution is the identification of treble innovation firms, an emerging type of firm configured as an integrated system of technological innovations in product, process, and digital service. These firms possess exploitative and exploratory innovative capabilities, a novel manufacturing archetype that fits the new digital paradigm and

Table 6
The effect of treble innovation on performance by groups.

Panel A. Testing resource retrenchment		
	Open innovation (above midpoint)	Open innovation (below midpoint)
R&D presence	Quadrant A1 ROS (treble) = 0.086 ROS (dual) = 0.041 p-value (|diff|>0) = 0.075*	Quadrant A2 ROS (treble) = 0.121 ROS (dual) = 0.072 p-value (|diff|>0) = 0.006***
R&D absence	Quadrant A3 ROS (treble) = 0.202 ROS (dual) = 0.056 p-value (|diff|>0) = 0.045**	Quadrant A4 ROS (treble) = 0.060 ROS (dual) = 0.084 p-value (|diff|>0) = 0.265
Panel B. Testing value migration		
	TFP (above mean)	TFP (below mean)
Product leadership (Market share >10%)	Quadrant B1 ROS (treble) = 0.083 ROS (dual) = 0.099 p-value (|diff|>0) = 0.265	Quadrant B2 ROS (treble) = 0.213 ROS (dual) = 0.085 p-value (|diff|>0) = 0.048**
No product leadership (Market share <10%)	Quadrant B3 ROS (treble) = 0.087 ROS (dual) = 0.063 p-value (|diff|>0) = 0.129	Quadrant B4 ROS (treble) = 0.094 ROS (dual) = 0.053 p-value (|diff|>0) = 0.113

Notes. The analysis was conducted using the matched sample obtained with 1:1 nearest neighbor. Results with the other matched subsample are qualitatively the same. *$p < 0.1$. **$p < 0.05$. ***$p < 0.01$.

has not been identified to date or discussed in the management literature. Our study clarifies the configuration of this new type of firm by examining antecedents, outcomes, and enhancers. The results suggest that antecedents such as product leadership, open innovation, and large customer base increase the probability that dual innovators will implement digital service innovation. After PSM treatment correction, profit margins were superior among treble innovation firms, and findings on enhancers indicate that resource retrenchment and value migration were crucial to determining treble innovation firms' profit advantage. The results have implications for three theoretical domains.

First, regarding organizational ambidexterity (Raisch and Birkinshaw, 2008; Turner et al., 2013), this study responds to calls for inclusion of ambidexterity in firm's technological operations (e.g., O'Reilly and Tushman, 2013) by developing a distinctive approach to innovation (i.e., exploitation and exploration) that characterize treble innovation firms. We argue for pursuit of an ambidextrous orientation in which constant exploration of new digital service solutions, aimed at closer relationships with customers, is complemented by continuous exploitation of product and process innovations to strengthen operational efficiency and product improvement (Vrontis et al., 2017). This framework has three implications for ambidexterity research. First, it suggests that ambidexterity is contingent on the technologies available at each historical moment (see Fig. 2). It is necessary therefore to conceptualize ambidexterity as a dynamic construct that needs to be redefined depending on the state of technology. Second, it corroborates that servitized manufacturers face a context-specific type of ambidexterity (e.g., Bustinza et al., 2020) that possesses exploitative product and process innovation and exploratory digital service innovation. Third, it opens opportunities for future research on ambidexterity within the realm of technological innovation management. One such opportunity would be to assess mechanisms behind the development of ambidextrous capabilities in the digital era through case study research (e.g., Hsuan et al., 2021), as such study could help to unveil specific examples of treble innovation in diverse settings and types of firms.

Second, the analysis contributes to our understanding of service implementation in manufacturing industries (e.g., Visnjic-Kastalli and Van Looy, 2013; Baines et al., 2017). The current study suggests that digital service innovation is the last step in the technological evolution of manufacturing companies in adopting a competitive treble innovation strategy. This approach not only differs from standard models of technological innovation based on dual configuration (Bstieler et al., 2018; Cornelius et al., 2021) but also diverges from the digital servitization literature on the adoption of digital services as a business model innovation rather than a technological innovation (e.g., Coreynen et al., 2017; Gebauer et al., 2021) and responds to calls for more research incorporating technological (Snyder et al., 2016; Witell et al., 2016) and digital (Barrett et al., 2015) elements in service innovation.

Finally, this study contributes to the linkage between open innovation (Chesbrough, 2003; Gassmann et al., 2010) and the RBV (Barney, 1991; Sirmon et al., 2007), a topic that has gained traction recently (see Alexy et al.'s, 2018). We demonstrate that by engaging with external sources of innovation (i.e., open innovation), treble innovation firms can achieve their triad of innovation goals (product, process, and digital service) without stretching internal R&D resources (i.e., resource retrenchment). We also show that treble innovation firms with product leadership can migrate value from process to service innovation, increasing profit (i.e., value migration). Although the importance of the RBV to the firm's innovation strategy is well-documented (Chahal et al., 2020), our results open opportunities for future research that may further explore relationships among innovation management and the RBV. For instance, our evidence supports resource retrenchment. That is, investment in internal R&D can be replaced by open innovation, opposing other views suggesting that internal R&D complements external knowledge (Cassiman and Veugelers, 2006). Future research should explore ways to reconcile this apparent contradiction. As to value migration, current results suggest that treble innovation firms can migrate value from shared to proprietary resources, but we cannot explain how such migration occurs—a topic for future qualitative research.

From a managerial perspective, the study results improve directors', production managers', and innovation managers' understanding of the applicable constituents in a treble innovation strategy that results in greater competitiveness and profits. The results reinforce the relevance of demand-side strategies, such as accentuating collaboration with customers and offering customization to enable firms to explore solutions that encourage adoption of digitally-enabled service innovation. Practitioners searching for performance benefits ought to consider openness as a substitute for internal R&D expenditures and not a complementary strategy itself.

6.2. Limitations

Cross-sectional data enabled us to assess whether innovations are simultaneously relevant to innovation processes in treble innovation firms, but not whether order of adoption matters. Future research should assess whether integration of innovations in terms of product, process, and digital service innovation are linear and planned, or follow any other patterns. Likewise, as cross-sectional data did not permit us to analyze the long-term benefits of a strategy, longitudinal research should assess long-term performance of treble innovation strategies. As the manufacturing innovations assessed in this study were treated dichotomously, we were unable to control for differences in innovation intensity or quality. Future research that evaluates treble innovation firms should consider such differentiations, for example, by uncovering the specific performance-enhancing effect of each type of digital service innovation (e.g., Tao et al., 2014). Moreover, although this study argues that product leadership leads innovators straight into higher market shares (Sutton, 2007), product leadership may not be the only cause of higher market share. Future studies may need to use other proxies of product leadership to ensure the strength of the hypothesized relationship.

The main objective of this study was to understand the paradigm shifts in technological innovation that the combination of digitalization and service provision have caused in manufacturing companies. To this aim, we proposed a historical perspective of the dominant models of strategic ambidexterity during different times. Such an approach, focused on organizational-level heterogeneities rather than identifying common patterns, is unusual in the ambidexterity literature. However, this novel vision is not without limitations. For example, it does not envision minority models that are still feasible in the digital era (e.g., explorative product and process innovation). To establish the relevance of dominant models of ambidextrous innovation at any given state of technology, a further line of inquiry would need to find out the relative weight of the dominant ambidexterity models in each period of time. Of course, this would require a more thorough theoretical inspection of the model described in this study.

Finally, the number of antecedents analyzed in the current study is comprehensive but focuses on demand-side factors that stimulate customer contact. Future research should investigate supply-side factors, including production volume and location, multi-product supply, financial constraints, and international strategy.

7. Conclusion

By examining the final stage in the evolution of ambidextrous technological innovation, this study offers insights that advance understanding of digitally-enabled, simultaneous process, product, and digital service innovation practices, a phenomenon for which this paper coins the term treble innovation. Findings should encourage researchers to examine critically the relevance of extant theories in modern manufacturing firms and the emergence of treble innovation strategies.

Data availability

The data that has been used is confidential.

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