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Innovation Performance in the Era of Industry 4.0 and Open Innovation

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Abstract
This study examines the individual and combined effects of digitalization and inbound open innovation (OI) on technological innovation, specifically product and process innovation, among German firms. Digitalization is represented by the adoption of artificial intelligence (AI) and big data analytics (BDA), while inbound OI is measured through the breadth of external knowledge search. The analysis utilizes data from the 2019 wave of the Mannheim Innovation Panel, covering the period 2016–2018, and applies econometric techniques to investigate these relationships across both manufacturing and service sectors. The findings reveal heterogeneous effects of digitalization on innovation outcomes. AI is found to positively influence product innovation, whereas BDA significantly increases the likelihood of process innovation. Furthermore, the results indicate that AI does not generate synergistic effects when combined with external knowledge search, while BDA appears to weaken the positive influence of search breadth on process innovation. These findings provide important theoretical, managerial, and policy insights regarding the role of digital technologies and open innovation practices in fostering innovation performance. This study contributes to the literature by offering a comprehensive perspective on how digitalization and inbound OI interact to shape technological innovation and by highlighting sectoral differences between manufacturing and service firms in Germany.

Keywords: Open Innovation; Digitalization; Artificial Intelligence; Big Data Analytics; Technological Innovation.

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1. Introduction

Innovation is widely recognized as a fundamental driver of socio-economic development because it supports employment generation, investment growth, and overall economic competitiveness (OECD, 2022). At the firm level, innovation plays a critical role in ensuring organizational survival and long-term growth (Cefis et al., 2020; Nogueira et al., 2018; Visnjic et al., 2014; Jong, 2013). Conversely, firms that fail to innovate often face difficulties in maintaining competitiveness in both domestic and international markets and may ultimately struggle to survive (Ratten, 2015; Wilkinson & Thomas, 2014). The development of new products, services, and operational processes is therefore essential for entrepreneurial success and business sustainability (Neumeyer et al., 2021). Furthermore, organizations that simultaneously pursue product and process innovation are more likely to strengthen their market position and improve their prospects for long-term survival (Colombelli et al., 2016; Kafetzopoulos et al., 2015).

The integration of information technology (IT) and research and development (R&D) activities has been shown to generate superior productivity growth and enhance firm performance (Khanna & Sharma, 2021). IT resources contribute to knowledge creation and diffusion through multiple channels, producing productivity gains and supporting organizational competitiveness (Kılıçaslan et al., 2017; Marsh et al., 2017). However, many firms lack sufficient technological knowledge to effectively develop innovative products and processes. As a result, organizations differ substantially in their adoption of technological solutions, reflecting variations in implementation intensity, innovation orientation, and organizational capabilities (Frank et al., 2019). In this context, digitalization has emerged as an important mechanism for facilitating innovation and technological development.

Digitalization is closely associated with the concept of Industry 4.0, which generally refers to the transformation of industrial systems through automation, digital integration, and servitization (Yun et al., 2021). Industry 4.0 encompasses a broad range of technologies, including big data analytics (BDA), artificial intelligence (AI), autonomous robots, simulation, horizontal and vertical system integration, industrial internet of things, cybersecurity, cloud computing, additive manufacturing, and augmented reality (R€ußmann et al., 2015). The adoption of these technologies typically requires significant investments in both physical and human capital (Davies, 2015). Consequently, firms experiencing financial constraints are often less likely to adopt Industry 4.0 technologies (Petruzzelli et al., 2021). Nevertheless, organizations seeking innovation benefits may pursue less costly and less risky alternatives by improving innovation management practices and leveraging external knowledge sources (Rammer et al., 2009).

Advancements in digital technologies have created new opportunities for firms to collect, process, and analyze large volumes of data. These capabilities can improve organizational performance, although they often require changes in managerial decision-making processes and greater collaboration across organizational functions (Frisk & Bannister, 2017). Digital technologies also enable manufacturers to produce customized products at competitive costs, thereby enhancing operational flexibility and competitiveness (Lorenz et al., 2020). The increasing emphasis on digital transformation reflects the belief that emerging technologies can become important sources of innovation and sustainable competitive advantage (Solberg et al., 2020). In addition, digital trust generated through Industry 4.0 technologies can facilitate open innovation activities by encouraging collaboration and knowledge exchange among organizations (Mubarak & Petraite, 2020).

Open innovation (OI), defined as the deliberate use of external knowledge inflows to accelerate internal innovation processes (Chesbrough, 2003), has been extensively examined in innovation research. Likewise, digitalization, particularly through technologies such as AI and BDA, has emerged as a transformative force that enables firms to process information more effectively, optimize operations, and create innovative products and services (Brynjolfsson & McAfee, 2017). Although previous studies have documented the positive effects of OI and digitalization separately, their combined influence on technological innovation remains insufficiently explored, particularly in the context of German firms. Therefore, this study investigates whether digitalization strengthens the established relationship between inbound open innovation practices—specifically search breadth—and technological innovation outcomes.

Prior research has largely treated digitalization and open innovation as independent phenomena, overlooking their potential complementary effects (West & Bogers, 2014). For example, Laursen and Salter (2006) demonstrated that search breadth positively influences innovation performance; however, their framework does not account for how digital technologies such as AI and BDA may reinforce this relationship within Industry 4.0 environments (Lorenz et al., 2020). Similarly, studies examining digitalization have focused primarily on the standalone effects of AI and BDA (Rammer et al., 2022), while paying limited attention to their interaction with external knowledge sourcing strategies.

This study addresses this gap by examining the joint influence of digitalization and inbound open innovation on technological innovation, particularly product and process innovation. Two forms of digitalization—artificial intelligence and big data analytics—are analyzed alongside search breadth, which captures the diversity of external partners involved in firms' innovation activities. Search breadth was originally conceptualized by Laursen and Salter (2006) and has since become one of the most widely applied measures of inbound open innovation (Petruzzelli et al., 2021). Although open innovation is frequently incorporated into Industry 4.0 readiness frameworks (Prause, 2015; Schumacher et al., 2016), limited empirical evidence exists regarding its synergistic effects with digitalization on innovation outcomes (Petruzzelli et al., 2021; Lorenz et al., 2020).

The theoretical rationale for investigating this relationship lies in the complementary nature of digitalization and open innovation. Search breadth enables firms to access diverse external knowledge sources; however, the increasing complexity and volume of information may create cognitive and organizational challenges (Laursen & Salter, 2006). Digital technologies such as AI and BDA can alleviate these constraints by facilitating knowledge identification, opportunity recognition, and large-scale data analysis, thereby enhancing firms' absorptive capacity (Ghasemaghaei & Calic, 2020). Consequently, digitalization may amplify the benefits of open innovation, generating innovation outcomes that exceed the individual contributions of each approach.

Given Germany's highly industrialized and export-oriented economy, as well as its strong commitment to digital transformation and innovation policies (Rammer et al., 2022; OECD, 2022), it provides an appropriate setting for investigating the interaction between digitalization and open innovation. Therefore, this study seeks to answer three research questions: (1) Do digitalization and inbound open innovation contribute to firms' product and process innovation activities? (2) Does digitalization strengthen the impact of inbound open innovation on innovation outcomes? and (3) Do these effects differ between manufacturing and service firms? Using data from the Mannheim Innovation Panel (MIP), particularly the 2019 survey wave covering innovation activities during the 2016–2018 period, this study contributes to the literature by integrating the open innovation and digitalization perspectives while also examining sectoral differences between manufacturing and service firms. The findings are expected to enrich understanding of how firms can leverage digital capabilities and external knowledge sources to enhance technological innovation performance.

2. Literature Review

Businesses of all sizes are required to continuously and systematically search for innovation opportunities. Product innovation is commonly associated with long-term research and development activities, whereas process innovation tends to be less formalized, requires less scientific infrastructure, and is generally more short-term oriented (Radicic & Alkaraan, 2022). Although the literature on technological innovation has largely emphasized product innovation, product and process innovations are often regarded as complementary forms of innovation (Reichstein & Salter, 2006; Ayllón &

Radicic, 2019). However, many studies still examine these innovation types separately and pay limited attention to how external knowledge and digital technologies may support both product and process innovation simultaneously (Hullova et al., 2016).

Developing external linkages requires network competence, including the ability to identify innovation impulses from customers, leverage suppliers as innovation sources, and absorb knowledge from other organizations, competitors, and public research institutions (Rammer et al., 2009). Industry 4.0 technologies, such as artificial intelligence, big data, blockchain, cyber-physical systems, and the Internet of Things, have accelerated technological transformation and business internationalization (Sung, 2018). Through advanced cyber-physical systems and digital infrastructures, these technologies can improve productivity and innovation performance (Mubarak & Petraite, 2020). However, digital transformation requires motivated and digitally skilled employees, substantial investment in equipment, and knowledge spillovers from open innovation sources.

Firms cannot accelerate innovation solely by relying on internal resources. Therefore, many organizations increasingly adopt open innovation strategies by collaborating with external stakeholders (Mubarak & Petraite, 2020). Open innovation has become part of firms' innovation practice portfolios and represents a viable alternative to closed innovation models (Ooms & Piepenbrink, 2020). It refers to firms' ability to use both internal and external ideas, as well as internal and external paths to market, to advance technological development (Chesbrough, 2003; Ghasemaghaei & Calic, 2019). Nevertheless, open innovation also presents challenges, including higher coordination and transaction costs, increased collaboration complexity, and risks of knowledge leakage to competitors (Greco et al., 2019; West & Bogers, 2014). Excessive dependence on external sources may also weaken internal innovation capabilities or lead to over-search, where the costs of processing diverse knowledge inputs exceed their benefits (Chaudhary et al., 2022; Laursen & Salter, 2006).

The need for both digital transformation and open innovation is driven by the complexity of digital technologies. Because firms cannot easily master all opportunities offered by digital technologies, they need access to external knowledge and collaborative innovation networks (World Economic Forum, 2018). Open innovation is not limited to product innovation but also applies to process innovation, as reflected in the concept of open process innovation (Von Krogh et al., 2018). Process innovations are essential for improving productivity, efficiency, and economic growth (Terjesen & Patel, 2017).

Open innovation activities can be divided into inbound, outbound, and coupled knowledge transfer processes (Enkel et al., 2009). Inbound open innovation refers to purposive inflows of knowledge that support technology exploration and innovation activities through external knowledge sources (Mazzola et al., 2012). Outbound open innovation involves relationships with external partners to commercialize ideas and technological opportunities more rapidly. Coupled open innovation combines inbound and outbound processes to jointly develop and commercialize innovation (Mazzola et al., 2012). Inbound and outbound practices are often considered informal forms of external knowledge use, while coupled open innovation refers to formal cooperative networking such as strategic alliances and joint ventures (Gassmann & Enkel, 2004; Radicic, 2021; Radicic & Alkaraan, 2022).

External knowledge may improve innovation performance when firms are able to process and combine it with internal expertise (Weissenberger-Eibl & Hampel, 2021). Search breadth refers to the number and diversity of external knowledge sources used by firms in their innovation processes (Laursen & Salter, 2006). It enables firms to obtain ideas from various knowledge sources, and both SMEs and large firms may benefit from knowledge flows across organizational boundaries (Lorenz et al., 2020). Relationships with research centers, technology parks, and innovation agencies can help firms access knowledge, resources, and assets while encouraging the exchange of best practices and overcoming managerial resistance toward new technologies (Zangiacomi et al., 2020).

Innovation and knowledge are widely recognized as key foundations of competitiveness and economic growth (Piñeiro-Chousa et al., 2020). Process innovation refers to the implementation of new or significantly improved production or delivery methods, including changes in techniques, equipment, or software (OECD, 2005). More recently, OECD/Eurostat (2018) defined process innovation as a new or improved business process that differs significantly from a firm's previous processes and has been implemented by the firm. Product innovation refers to the introduction of new or improved goods or services that differ significantly from previous offerings. Despite these definitions, prior studies often fail to distinguish clearly between product and process innovation when assessing the impact of open innovation, leading to mixed findings across innovation types (Hervas-Oliver et al., 2021).

The effectiveness of open innovation depends on the transition from a closed innovation system to an open innovation paradigm, which can enhance innovation performance through stronger interaction with external ecosystem actors (Mubarak & Petraite, 2020). Open innovation enables firms to shorten cycles of ideation, prototyping, development, and commercialization while increasing both exploration and exploitation opportunities (Salampasis & Mention, 2019). Absorptive capacity also plays an important role in implementing inbound open innovation because firms must recognize, assimilate, and apply external knowledge effectively (Cohen & Levinthal, 1990).

This study examines the influence of inbound open innovation, operationalized as search breadth, on product and process innovation. Although search depth is also an important concept in open innovation research, it is not investigated due to data limitations. Search breadth is measured using eight external information sources from the Mannheim Innovation Panel, including customers, suppliers, competitors, consultants, universities, research institutes, conferences, and trade fairs or exhibitions. These sources reflect purposive knowledge inflows from diverse external actors (Chesbrough, 2003), distinguishing open innovation from closed innovation, where external knowledge is used less systematically (West & Bogers, 2014). Prior studies have also categorized external linkages based on their openness, including sourcing, market path, and shared activities (Öberg & Alexander, 2019), while other research has measured search breadth and depth using multiple external knowledge sources such as professional conferences, fairs, and exhibitions (Ferraris et al., 2020).

Previous empirical findings on search breadth remain mixed. Zhao (2021) found that the breadth of platform openness does not moderate the relationship between open innovation and innovation performance, whereas depth has a positive moderating effect. Chou et al. (2016) showed that coupled open innovation improves incremental performance outcomes but not radical outcomes, particularly when supported by absorptive capacity. Terjesen and Patel (2017) found that search breadth negatively affects process innovation, while search depth positively affects process innovation. Based on this evidence, this study proposes that the breadth of inbound open innovation positively influences the likelihood of product and process innovation.

This study also distinguishes between manufacturing and service firms. Innovation research has developed three perspectives regarding sectoral differences: the assimilation approach, the demarcation approach, and the synthesis approach (Radicic, 2021). The assimilation approach assumes that innovation activities are broadly similar across manufacturing and service sectors (Radicic, 2021; Wong & He, 2005). The demarcation approach emphasizes the distinct characteristics of service innovation and argues that service-specific concepts and models are needed (Cainelli et al., 2020; Wong & He, 2005). The synthesis approach suggests that manufacturing and service innovations share some characteristics while also exhibiting important differences. This study follows the synthesis perspective by examining the full sample as well as separate manufacturing and service subsamples.

The resource-based view highlights the importance of internal resources for innovation across sectors. However, recent research also emphasizes that open innovation and knowledge exchange with external environments are highly relevant in both manufacturing and service industries (Cainelli et al., 2020; Mina et al., 2014; Radicic, 2021). Service firms, in particular, are more likely to engage in informal knowledge exchange with external sources rather than formal contractual cooperation (Mina et al., 2014). Prior empirical studies also show sectoral differences. Laursen and Salter (2006) found a curvilinear relationship between search breadth and product innovation in UK manufacturing firms, whereas Terjesen and Patel (2017) reported a negative effect of search breadth on process innovation. Cainelli et al. (2020) found that external knowledge search breadth is more important for knowledge-intensive business services than for high-tech manufacturing firms. Leiponen (2012) showed that both manufacturing and service firms benefit from diverse information flows from multiple knowledge sources. Therefore, this study expects inbound open innovation breadth to increase the likelihood of product and process innovation in both manufacturing and service sectors.

The impact of digitalization on innovation can be explained through organizational learning theory, which builds on the resource-based view by arguing that unique, valuable, inimitable, and non-substitutable resources support competitive advantage (Barney, 1991; Huber, 1991). In innovation activities, organizational learning theory emphasizes that searching for and adopting new information are essential foundations for innovation (Johnson et al., 2017; Ghasemaghaei & Calic, 2020). Firms collect data from various sources, process and interpret them, and use them to develop or improve products and processes. This integration of data and information into organizational operations represents a form of organizational learning (Ghasemaghaei & Calic, 2020).

Big data analytics, as one of the pillars of Industry 4.0, can enhance organizational learning by allowing firms to analyze large volumes of data quickly and efficiently. It can expand firms' knowledge base and innovation capabilities (Ghasemaghaei & Calic, 2020). Artificial intelligence can also facilitate information exploration, organizational learning, absorptive capacity, and knowledge base expansion (Liu et al., 2020). AI supports innovation by accelerating knowledge creation, generating knowledge and technology spillovers, improving learning and absorption capacities, and encouraging investment in R&D and talent (Liu et al., 2020). AI can also facilitate open innovation by improving inbound and outbound knowledge flows and helping managers combine existing knowledge to support innovation, organizational performance, and financial performance (Liu et al., 2020).

Identification technologies, such as barcodes, sensors, radio-frequency identification, and near-field communication, enable contactless tracking of production processes and products (Xu et al., 2018). These data form part of big data, which can be analyzed using statistical methods or machine learning algorithms (Brinch, 2018; Kache & Seuring, 2017; Matthias et al., 2017). Big data technologies can capture, transmit, store, and analyze structured and unstructured data to support managerial decision-making (Vidgen, 2020). Disruptive technologies such as the Internet of Things, mobile technologies, big data, and AI continue to reshape operational environments and transform business models (Chege et al., 2020; Langley et al., 2021).

BDA can improve open innovation processes by helping firms assess supplier reputation, partner reliability, and stakeholder trustworthiness based on past performance, business portfolios, and collaboration histories (Mubarak & Petraite, 2020). It can also support the selection of appropriate suppliers, partners, co-creators, and collaborators while streamlining processes and reducing bottlenecks (Davenport, 2014; Mubarak & Petraite, 2020). However, BDA infrastructure requires substantial investment (Wang & Hajli, 2017). Strong data resources and managerial skills are crucial for achieving radical process innovation capabilities (Mikalef & Krogstie, 2020). Prior research also indicates that BDA enables incremental and radical process innovation and supports radical product innovation through data analytics when decentralization and local autonomy are present (Mikalef & Krogstie, 2020; Rammer et al., 2022; Slater et al., 2014). Accordingly, this study proposes that firms using AI and BDA are more likely to engage in product and process innovation.

AI and BDA may influence both manufacturing and service sectors. Although much AI research has focused on manufacturing, AI is increasingly important in service operations digitalization (Mariani & Borghi, 2023). Concepts such as smart manufacturing and smart services have emerged to describe the use of data-based technologies in production and service contexts (Phuyal et al., 2020; Tao et al., 2018; Wuenderlich et al., 2015). In manufacturing, AI supports data-based business models that collect and analyze consumer behavior and product-use data, which can inform decision-making and innovation activities (Rammer et al., 2022). Empirical evidence on AI and innovation remains limited, particularly in service industries, although existing studies examine manufacturing or combined manufacturing and service samples (Cockburn et al., 2019; Liu et al., 2020; Rammer et al., 2022). BDA also assists firms in analyzing internal and external data, automating service processes, understanding current and future customer needs, and identifying new market opportunities (Capurro et al., 2022; Lehrer et al., 2018; Mariani et al., 2023). These mechanisms can support new products, processes, and services in both sectors (Duan et al., 2020). Therefore, this study expects AI and BDA to positively influence product and process innovation in manufacturing and service sectors.

The relationship between Industry 4.0 and open innovation is increasingly important, yet remains insufficiently explored (Mubarak & Petraite, 2020). Lorenz et al. (2020) found no significant correlation between external search breadth and adoption of digital technologies, suggesting that firms may benefit more from strong ties with fewer external knowledge partners than from many weak relationships. They further argued that search depth is more important than search breadth for digitization in manufacturing firms. In contrast, Petruzzelli et al. (2021) found that open innovation breadth and depth may both be positively associated with Industry 4.0 technology adoption. The technological intensity of industries may also moderate the relationship between open innovation depth and Industry 4.0 implementation (Dahiya et al., 2021; Urbinati et al., 2019).

Digital trust is another mechanism linking Industry 4.0 and open innovation. It refers to the integration of Industry 4.0 technologies, such as BDA, Internet of Things, blockchain, and cyber-physical systems, with traditional dimensions of trust (Mubarak & Petraite, 2020). Digital trust can strengthen collaboration among firms within innovation networks and accelerate open innovation processes (Mubarak & Petraite, 2020). Furthermore, manufacturing flexibility combined with process or organizational innovation may increase firms' engagement in product innovation (Torres & Augusto, 2019). In the digitalization context, open innovation is expected to become an increasingly important research theme (Enkel et al., 2020). Although some studies link open innovation and BDA through specific analytical techniques for generating innovation ideas (Ciampi et al., 2021; Urbinati et al., 2019; Wen et al., 2020), fewer studies examine the relationship between BDA and open innovation acquisition processes from a broader strategic perspective (Arias-Pérez et al., 2022). Therefore, this study expects AI and BDA to strengthen the impact of inbound open innovation breadth on product and process innovation, both in the full sample and in manufacturing and service sectors.

3. Research Methods

This study uses data from the Mannheim Innovation Panel (MIP), collected by the Centre for European Economic Research in collaboration with the Fraunhofer Institute for Systems and Innovation Research and the Institute for Applied Social Sciences on behalf of the German Federal Ministry of Education and Research. The MIP is an annual innovation survey based on a panel sample of German firms and represents Germany's contribution to the European Commission's Community Innovation Survey. The analysis focuses on the 2019 survey wave because it contains information on firms' digitalization activities and covers the innovation period from 2016 to 2018 (Rammer et al., 2022). The final sample for econometric analysis consists of 1,374 firms, including 706 manufacturing firms and 668 service firms.

The dependent variables are product innovation and process innovation. Product innovation is coded as 1 if a firm introduced new or improved products or services during 2016–2018 that differed significantly from previous offerings, and 0 otherwise (Hervas-Oliver et al., 2021; Niebel et al., 2019; Radicic & Petković, 2023). Process innovation is coded as 1 if a firm introduced new or improved processes during 2016–2018, including production methods, service delivery methods, logistics, distribution, information processing, communication, accounting, or administrative operations, and 0 otherwise (Hervas-Oliver et al., 2021; Radicic & Petković, 2023).

Inbound open innovation is measured using the variable Breadth, which captures the number of external knowledge sources used by a firm (Laursen & Salter, 2006; Radicic, 2021). The variable ranges from 0 if a firm uses no external knowledge source to 8 if it uses all eight sources. These sources include conferences, trade fairs or exhibitions; scientific or technical journals and trade publications; patent files; standardization documents or committees; social web-based networks or crowdsourcing; open-source software and open business platforms; reverse engineering; and recruitment of employees bringing relevant know-how from other enterprises.

Digitalization is measured through AI and BDA. AI is coded as 1 if a firm uses artificial intelligence methods and 0 otherwise (Liu et al., 2020; Rammer et al., 2022). BDA is coded as 1 if a firm conducted systematic big data analysis related to software and databases during 2016–2018, and 0 otherwise (Niebel et al., 2019; Radicic & Petković, 2023). Control variables include Continuous R&D, which is coded as 1 for firms that continuously engage in R&D activities and 0 otherwise (Douglas & Radicic, 2022; Mairesse & Mohnen, 2004; Radicic, 2021); Firm size, measured as the natural logarithm of the number of employees in 2017 (Petruzzelli et al., 2021; Rammer et al., 2022); Export intensity, measured as the share of total revenue from foreign markets in 2017 (Busom & Fernández-Ribas, 2008; Radicic, 2020; Radicic et al., 2019); University degree, measured as a categorical indicator of the share of employees holding a university degree and used as a proxy for human capital (Leiponen, 2005; Rammer et al., 2022); and sector dummy variables for 20 sectors.

Table 1. Descriptive Statistics

Variable	Full Sample Mean	Full Sample SD	Manufacturing Mean	Manufacturing SD	Services Mean	Services SD
Product innovation	0.429	0.495	0.455	0.498	0.403	0.491
Process innovation	0.451	0.496	0.465	0.499	0.437	0.496
AI	0.063	0.242	0.052	0.223	0.073	0.261
BDA	0.180	0.384	0.152	0.359	0.210	0.407
Search breadth	2.996	1.883	2.530	1.945	3.254	1.807
Continuous R&D	0.205	0.404	0.265	0.442	0.142	0.350
Exports	0.134	0.344	0.208	0.277	0.055	0.170
University degree	1.271	1.169	1.113	0.911	1.644	1.339
Firm size	79.203	154.809	91.227	164.191	66.495	143.260
Textiles, clothing and leather products	0.033	0.178	0.064	0.244	–	–
Wood, paper and printing	0.035	0.184	0.068	0.252	–	–

Variable	Full Sample Mean	Full Sample SD	Manufacturing Mean	Manufacturing SD	Services Mean	Services SD
Refined petroleum, coke manufacture, chemical industry	0.029	0.168	0.057	0.231	–	–
Manufacture of rubber and plastic products	0.034	0.182	0.067	0.249	–	–
Glass, ceramics, other non-metallic mineral products	0.029	0.168	0.057	0.231	–	–
Manufacture of basic metals and fabricated metal products; steel, metal structures	0.087	0.282	0.170	0.376	–	–
Manufacturing of office machinery and computers, electrical machinery and apparatus, radio, television and communication equipment	0.071	0.256	0.137	0.345	–	–
Manufacturing of machinery, weapons and ammunition, domestic appliances	0.039	0.193	0.075	0.264	–	–
Automotive industry	0.021	0.144	0.041	0.199	–	–
Manufacturing of furniture, jewellery, musical instruments, sports equipment, games and toys	0.078	0.268	0.151	0.359	–	–
Wholesale	0.043	0.203	–	–	0.088	0.284
Transport equipment and postal services	0.103	0.305	–	–	0.213	0.409
Media services	0.047	0.211	–	–	0.096	0.295
IT and telecommunications	0.099	0.293	–	–	0.079	0.270
Banking and insurance	0.044	0.204	–	–	0.090	0.286
Technical and R&D services	0.071	0.257	–	–	0.147	0.354
Consulting and advertisement	0.069	0.254	–	–	0.142	0.350
Firm-related services	0.070	0.256	–	–	0.145	0.353

Table 1 presents variable descriptions and summary statistics. Overall, 42.9% of firms introduced product innovation and 45.1% introduced process innovation. Manufacturing firms were slightly more innovative than service firms, with product innovation rates of 45.5% and 40.3%, respectively, and process innovation rates of 46.5% and 43.7%. Regarding digitalization, 6.3% of firms used AI, with adoption slightly higher among service firms than manufacturing firms. Approximately 18% of firms used BDA, again with a higher share among service firms. On average, firms used two external knowledge sources. Around 20.5% of firms continuously engaged in R&D, with a higher share among manufacturing firms than service firms. Average export intensity was 13.4%, with manufacturing firms exporting more than service firms. The average share of employees with a university degree was below 20%, and the modal firm had 79 employees, indicating a medium-sized firm.

The empirical analysis is based on the knowledge production function introduced by Griliches (1979), which models firms' innovation output as a function of knowledge-related inputs such as R&D activities, open innovation strategies, human capital, and digital technologies (Niebel et al., 2019; Radicic, 2021; Sarbu, 2021). This framework allows the analysis of whether knowledge sources beyond formal R&D contribute to innovation outcomes (Sarbu, 2021). Since the dependent variables are binary indicators of product and process innovation, logit models are estimated (Gao et al., 2022; Rammer et al., 2022). Separate estimations are also conducted for manufacturing and service firms to examine sectoral heterogeneity and assess whether the results support the assimilation, demarcation, or synthesis perspective of innovation.

4. Results

Because the data used in this study are self-reported, common method variance may arise from systematic measurement error (Podsakoff & Organ, 1986). To assess the internal validity of the dataset, Harmon's one-factor test was conducted (Podsakoff & Organ, 1986; Podsakoff et al., 2003). This test involved an exploratory factor analysis of all independent variables using unrotated principal component factor analysis. Common method bias is considered unlikely when the first unrotated factor accounts for less than 50% of the total variance among the explanatory variables. In this study, the first factor explained only 16.68% of the total variance, indicating that common method bias does not represent a serious concern in the empirical model (Tehseen et al., 2017).

Table 2. Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) AI	1.000						
(2) BDA	0.294	1.000					
(3) Search breadth	0.225	0.373	1.000				
(4) Continuous R&D	0.181	0.283	0.428	1.000			
(5) Exports	0.163	0.171	0.328	0.371	1.000		
(6) University degree	0.152	0.194	0.269	0.275	0.110	1.000	
(7) Firm size	0.135	0.355	0.400	0.350	0.342	−0.021	1.000

Table 2 presents the Pearson correlation matrix among the independent variables. Overall, the correlation coefficients are low to moderate, suggesting that multicollinearity is unlikely to affect the estimation results.

Table 3. Logit Models without Interaction Terms – Testing H1, H2, H3 and H4

Variables	Full Sample Product Innovation	Full Sample Process Innovation	Manufacturing Product Innovation	Manufacturing Process Innovation	Services Product Innovation	Services Process Innovation
Variables of Interest						
AI	0.853*** (0.325)	0.480 (0.334)	0.771 (0.501)	0.058 (0.471)	0.943** (0.432)	0.708 (0.455)
BDA	0.167 (0.192)	0.913*** (0.196)	0.071 (0.286)	1.250*** (0.330)	0.232 (0.257)	0.692*** (0.252)
Search breadth	0.280*** (0.041)	0.366*** (0.042)	0.190*** (0.057)	0.326*** (0.061)	0.363*** (0.059)	0.407*** (0.058)
Control Variables						
Continuous R&D	1.246*** (0.190)	0.677*** (0.193)	1.402*** (0.247)	0.617** (0.248)	1.102*** (0.305)	0.836** (0.327)
Exports	0.434 (0.327)	−0.112 (0.336)	0.573 (0.408)	0.078 (0.400)	0.381 (0.625)	−0.289 (0.665)
University degree	0.036 (0.066)	−0.070 (0.067)	0.080 (0.111)	−0.099 (0.112)	−0.002 (0.084)	−0.055 (0.083)
Firm size	−0.033 (0.050)	0.140*** (0.050)	−0.041 (0.074)	0.118 (0.074)	−0.036 (0.070)	0.161** (0.069)
Constant	−1.399*** (0.283)	−2.005*** (0.288)	−1.253*** (0.329)	−2.079*** (0.348)	−1.536*** (0.337)	−2.175*** (0.342)

Sector dummies	Included	Included	Included	Included	Included	Included
No. of observations	1,385	1,374	711	706	674	668

Notes: Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.10.

Table 3 reports the results of the logit models used to test H1, H2, H3, and H4. With respect to H1 and H2, search breadth, which captures inbound open innovation practices, positively increases the likelihood of both product innovation and process innovation in the full sample, as well as in the manufacturing and service subsamples. The effect is statistically significant at the 1% level. Therefore, H1 and H2 are fully supported.

Regarding H3, which examines the innovation effects of AI and BDA in the full sample, the results show that AI has a positive and highly significant effect on the probability of product innovation. Meanwhile, BDA has a positive and highly significant effect on the probability of process innovation. These findings indicate heterogeneous effects of AI and BDA depending on the type of innovation. Thus, H3 is partially supported.

In the sectoral analysis related to H4, AI is found to increase the likelihood of product innovation in the service sector, while BDA increases the likelihood of process innovation in both manufacturing and service sectors. Accordingly, H4 is partially supported, as AI appears to be more strongly associated with product innovation, whereas BDA is more strongly linked to process innovation.

The control variables also provide relevant insights. Continuous investment in R&D activities increases the likelihood of both product and process innovation across manufacturing and service sectors. In addition, larger firms are more likely to engage in process innovation, whereas firm size does not appear to significantly affect the probability of product innovation.

Table 4. Logit Models with the Interaction between AI and Search Breadth – Testing H5 and H6

Variables	Full Sample Product Innovation	Full Sample Process Innovation	Manufacturing Product Innovation	Manufacturing Process Innovation	Services Product Innovation	Services Process Innovation
Variables of Interest						
AI	1.462** (0.621)	0.877 (0.660)	0.827 (0.982)	−0.241 (1.069)	1.908** (0.840)	1.413* (0.815)
Search breadth	0.289*** (0.041)	0.372*** (0.043)	0.191*** (0.058)	0.323*** (0.063)	0.382*** (0.060)	0.420*** (0.060)
AI × Search breadth	−0.185 (0.159)	−0.124 (0.163)	−0.015 (0.218)	0.082 (0.265)	−0.317 (0.237)	−0.242 (0.217)
BDA	0.163 (0.192)	0.910*** (0.196)	0.070 (0.286)	1.255*** (0.332)	0.226 (0.257)	0.687*** (0.253)
Control Variables						
Continuous R&D	1.261*** (0.191)	0.684*** (0.194)	1.403*** (0.247)	0.614** (0.248)	1.143*** (0.308)	0.867*** (0.328)
Exports	0.429 (0.327)	−0.111 (0.336)	0.573 (0.408)	0.079 (0.400)	0.381 (0.629)	−0.269 (0.661)
University degree	0.037 (0.066)	−0.069 (0.067)	0.080 (0.111)	−0.099 (0.112)	−0.002 (0.085)	−0.056 (0.083)
Firm size	−0.034 (0.050)	0.139*** (0.050)	−0.041 (0.074)	0.118 (0.074)	−0.038 (0.070)	0.159** (0.069)
Constant	−1.423*** (0.283)	−2.019*** (0.289)	−1.254*** (0.329)	−2.074*** (0.347)	−1.578*** (0.338)	−2.202*** (0.346)
Sector dummies	Included	Included	Included	Included	Included	Included
No. of observations	1,385	1,374	711	706	674	668

Notes: Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.10.

Table 4 presents the logit models including the interaction term between AI and search breadth. These interaction terms are used to test H5 and H6 regarding the moderating effect of AI on the relationship between inbound open innovation and technological innovation. The results show that the interaction terms are not statistically significant in the full sample or in the manufacturing and service subsamples. Therefore, the empirical evidence does not support H5 and H6 with respect to the moderating role of AI. The results for the control variables remain qualitatively consistent with those reported in Table 3.

Table 5. Logit Regression Results

Variables	Full Sample Product Innovation	Full Sample Process Innovation	Manufacturing Product Innovation	Manufacturing Process Innovation	Services Product Innovation	Services Process Innovation
Variables of Interest						
BDA	0.265 (0.355)	1.753*** (0.354)	0.159 (0.552)	2.407*** (0.623)	0.367 (0.475)	1.453*** (0.446)
Search breadth	0.285*** (0.045)	0.413*** (0.046)	0.194*** (0.062)	0.372*** (0.064)	0.373*** (0.066)	0.459*** (0.065)
BDA × Search breadth	−0.030 (0.093)	−0.273*** (0.097)	−0.024 (0.127)	−0.337** (0.150)	−0.045 (0.134)	−0.264** (0.132)
AI	0.850*** (0.324)	0.481 (0.327)	0.768 (0.498)	0.085 (0.449)	0.942** (0.431)	0.704 (0.451)
Control Variables						
Continuous R&D	1.249*** (0.190)	0.695*** (0.192)	1.406*** (0.248)	0.659*** (0.251)	1.101*** (0.304)	0.833*** (0.320)
Exports	0.435 (0.327)	−0.099 (0.334)	0.575 (0.408)	0.106 (0.398)	0.381 (0.622)	−0.284 (0.647)
University degree	0.036 (0.066)	−0.078 (0.067)	0.079 (0.111)	−0.101 (0.114)	−0.003 (0.084)	−0.067 (0.083)
Firm size	−0.033 (0.050)	0.140*** (0.051)	−0.042 (0.074)	0.111 (0.075)	−0.035 (0.070)	0.164** (0.069)
Constant	−1.415*** (0.287)	−2.144*** (0.298)	−1.259*** (0.331)	−2.153*** (0.352)	−1.563*** (0.348)	−2.321*** (0.358)
Sector dummies	Included	Included	Included	Included	Included	Included
No. of observations	1,385	1,374	711	706	674	668

Notes: Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.10.

Table 5 reports the logit models including the interaction terms between BDA and search breadth. These models test H5 and H6 by examining whether BDA strengthens the effect of inbound open innovation on technological innovation. The results indicate that BDA does not enhance the effect of search breadth on product innovation, as the interaction term is not statistically significant in the full sample or in the sectoral subsamples. However, the interaction term between BDA and search breadth is negative and statistically significant in models where process innovation is the dependent variable. This pattern is observed in the full sample as well as in both manufacturing and service subsamples. These findings suggest that the interaction between BDA and inbound open innovation may reduce the likelihood of process innovation, a result that requires further discussion in the following section.

5. Discussion

The findings of this study provide several important insights regarding the individual effects of open innovation (OI) and Industry 4.0 technologies, as well as their potential combined influence on technological innovation. First, the results indicate that search breadth consistently increases the probability of both product and process innovation. This positive relationship is observed not only in the full sample but also across manufacturing and service sectors, thereby supporting both H1 and H2. These findings suggest that firms that draw knowledge from a wider range of external sources are more likely to engage in technological innovation. The results are consistent with previous studies highlighting the innovation benefits of inbound OI (e.g., Ebersberger et al., 2021). Furthermore, the evidence across both manufacturing and service industries supports the synthesis perspective of innovation, which argues that innovation activities in different sectors share common underlying mechanisms despite sector-specific characteristics.

The second set of findings, related to H3 and H4, offers additional insights into the role of digitalization technologies in fostering innovation. The results reveal heterogeneous effects for artificial intelligence (AI) and big data analytics (BDA). AI is found to positively influence product innovation, particularly within service firms, but does not significantly affect process innovation. In contrast, BDA exhibits a strong and statistically significant positive impact on process innovation while showing no significant effect on product innovation. Similar patterns are observed in both manufacturing and service sectors. These findings partially align with Rammer et al. (2022), who reported positive effects of AI on both product and process innovation among German firms. However, the present study suggests that the innovation benefits of AI are more pronounced in service industries than in manufacturing sectors. This result is also consistent with Liu et al. (2020), who found no significant influence of AI on technological innovation in China's high-technology industries, while observing marginal positive effects in low-technology sectors. One possible explanation is that firms may need to reach a certain threshold of AI implementation before meaningful innovation outcomes emerge (Liu et al., 2020). At lower levels of adoption, AI may not yet generate knowledge beyond what is already derived from R&D activities and external knowledge sourcing.

The findings concerning BDA can also be interpreted through the lens of organizational learning and information-processing capabilities. Ghasemaghaei and Calic (2020) demonstrated that data variety and data velocity positively influence innovation performance, whereas data volume alone contributes little to innovation outcomes. Excessive information may exceed the cognitive processing capacity of managers and employees, thereby limiting the ability to transform data into actionable knowledge. This perspective may help explain the results of the present study, particularly the substitution effect identified between BDA and search breadth in relation to process innovation. While access to diverse external knowledge sources facilitates process innovation, intensive reliance on BDA may reduce the marginal value of broad external knowledge search. The large amount of information generated through BDA may create challenges for decision-makers who face bounded rationality constraints when interpreting and utilizing complex datasets. Consequently, firms that employ BDA extensively may depend less on a broad range of external knowledge sources when pursuing process innovation. These findings contribute to the growing literature on external knowledge sourcing by suggesting that digital analytical capabilities can partially substitute for extensive inbound OI practices. From a managerial perspective, the results imply that firms pursuing digital transformation may achieve greater innovation benefits by strengthening digital capabilities rather than continuously expanding external knowledge networks. Conversely, firms with limited digitalization capabilities may derive greater value from broadening their external knowledge search activities.

The study also examined the moderating role of Industry 4.0 technologies on the relationship between inbound OI and innovation outcomes, as proposed in H5 and H6. The empirical evidence indicates that AI does not significantly moderate the relationship between search breadth and either product or process innovation. This absence of moderation is observed across the full sample as well as within manufacturing and service sectors. Therefore, H5 and H6 are not supported with respect to the moderating effect of AI. These findings are not entirely unexpected given the relatively limited direct effect of AI observed in the previous analyses. A similar pattern emerges for BDA. Although BDA does not strengthen the effect of search breadth on product innovation, it appears to weaken the positive influence of search breadth on process innovation. Rather than generating complementary effects, the interaction between BDA and inbound OI suggests a substitution relationship in the context of process innovation.

Overall, these findings indicate that firms may need to develop two distinct but complementary capabilities before digitalization and OI can generate synergistic innovation outcomes. The first capability is absorptive capacity, which enables firms to identify, assimilate, and exploit external knowledge obtained through inbound OI activities. The positive effects of search breadth observed in this study demonstrate the importance of this capability for innovation performance. The second capability relates to the effective integration of digital technologies, particularly AI and BDA, into organizational processes and innovation activities. As Industry 4.0 technologies remain relatively new and central to ongoing digital and green transitions, firms may need to allocate additional financial, technological, and human resources to strengthen their digital capabilities. Organizations with limited digital maturity may struggle to process and utilize the large volume of information generated through digital technologies and multiple external knowledge sources. Likewise, managers may face difficulties in effectively interpreting and applying information derived from BDA, thereby limiting the potential synergies between digitalization and OI.

The findings also have broader policy implications. Digitalization policies play a crucial role in supporting firms' adoption of Industry 4.0 technologies and enabling them to realize benefits in terms of innovation performance, productivity, profitability, and competitive advantage. Particular attention should be directed toward AI adoption. The descriptive statistics reveal that firms are approximately three times more likely to use BDA than AI. This pattern suggests that AI implementation may require greater financial investment, technical expertise, and organizational readiness than BDA. Consequently, governments and policymakers should consider targeted support mechanisms, including tax incentives, subsidies, grants, and training programs, to assist firms that lag behind in AI adoption. Such initiatives could accelerate the diffusion of AI technologies and enhance firms' innovation capabilities, thereby contributing to broader economic competitiveness and digital transformation objectives.

6. Conclusions

This study examined the role of digitalization within the Industry 4.0 context in shaping firms' product and process innovation activities, both independently and in combination with inbound open innovation (OI). In addition, the analysis compared manufacturing and service firms to determine whether these relationships differ across sectors. The findings reveal that search breadth consistently increases the likelihood of both product and process innovation. Firms that draw knowledge from a broader range of external sources are more likely to engage in technological innovation, regardless of whether they operate in manufacturing or service industries. In contrast, the effects of digitalization technologies are more heterogeneous. Artificial intelligence (AI) positively influences product innovation, particularly within service firms, whereas big data analytics (BDA) exhibits stronger effects on process innovation across both manufacturing and service sectors. However, the results do not support the expectation that AI and BDA strengthen the positive impact of inbound OI on technological innovation. In particular, BDA appears to weaken the influence of external knowledge search on process innovation, suggesting a potential substitution effect between digital analytical capabilities and extensive knowledge sourcing activities.

The study contributes to the literature by integrating two important streams of research, namely Industry 4.0 and open innovation, within a unified framework. While previous studies have extensively examined the individual effects of digitalization and OI, limited attention has been devoted to understanding their joint influence on innovation outcomes. The findings provide empirical evidence regarding the innovation effects of AI and BDA and demonstrate that their role is more nuanced than commonly assumed. Furthermore, the results highlight similarities between manufacturing and service sectors, lending support to the synthesis perspective of innovation, although the impact of AI appears to be more sector-specific. From a policy perspective, the findings suggest that governments should continue supporting firms' digital transformation efforts, particularly by accelerating AI adoption through financial incentives, subsidies, grants, and capability-building programs. Given that AI adoption remains substantially lower than BDA adoption, reducing barriers related to costs, technical expertise, and organizational readiness may help firms realize greater innovation benefits.

The findings also offer important managerial implications. Although inbound OI remains an effective mechanism for stimulating innovation, managers should not assume that digital technologies automatically enhance the benefits of external knowledge sourcing. Instead, organizations need to develop strong digital capabilities alongside absorptive capacity to effectively utilize both internal and external knowledge resources. Firms should therefore invest in employee skills, data management capabilities, and organizational learning mechanisms that enable the effective use of AI and BDA in innovation processes. Managers should also carefully evaluate the balance between digitalization initiatives and external knowledge acquisition strategies, as excessive reliance on data-driven technologies may reduce the marginal value of broad knowledge search activities.

Several limitations should be acknowledged. First, the study relies on cross-sectional data, which limits the ability to examine long-term relationships between digitalization, OI, and innovation. Future research could employ longitudinal datasets to investigate how these relationships evolve over time. Second, the analysis focuses exclusively on technological innovation in the form of product and process innovation. Future studies may extend the investigation to non-technological innovations, including organizational, marketing, and business model innovations. Third, digitalization is a multidimensional concept, yet this study considers only AI and BDA. Future research could examine additional digital technologies, such as cloud computing, blockchain, and Internet of Things applications, as well as their interaction with different forms of OI, particularly coupled innovation practices. Finally, the rapid advancement of emerging technologies, including generative AI, highlights the need for more recent empirical evidence to better understand how new digital capabilities shape firms' innovation performance. Despite these limitations, this study contributes to the growing body of knowledge by providing empirical evidence on the interplay between digitalization and open innovation and their implications for technological innovation in contemporary firms.

References

Abou-Foul, M., Ruiz-Alba, J. L., & Soares, A. (2021). The Impact Of Digitalization And Servitization On The Financial Performance Of A Firm: An Empirical Analysis. *Production Planning & Control, 32*(12), 975–989. Https://Doi.Org/10.1080/09537287.2020.1780508

Arias-Pérez, J., Coronado-Medina, A., & Perdomo-Charry, G. (2022). Big Data Analytics Capability As A Mediator In The Impact Of Open Innovation On Firm Performance. *Journal Of Strategy And Management, 15*(1), 1–15. Https://Doi.Org/10.1108/JSMA-09-2020-0262

Ayllón, S., & Radicic, D. (2019). Product Innovation, Process Innovation And Export Propensity: Persistence, Complementarities And Feedback Effects In Spanish Firms. *Applied Economics, 51*(3), 3650–3664. Https://Doi.Org/10.1080/00036846.2019.1584376

Barney, J. (1991). Firm Resources And Sustained Competitive Advantage. *Journal Of Management, 17*(1), 99–120. Https://Doi.Org/10.1177/014920639101700108

Brinch, M. (2018). Understanding The Value Of Big Data In Supply Chain Management And Its Business Processes: Towards A Conceptual Framework. *International Journal Of Operations & Production Management, 38*(7), 1589–1614. Https://Doi.Org/10.1108/IJOPM-05-2017-0268

Brynjolfsson, E., & Mcafee, A. (2017). The Business Of Artificial Intelligence. *Harvard Business Review, 95*(4), 1–15. Https://Hbr.Org/2017/07/The-Business-Of-Artificial-Intelligence

Busom, I., & Fernandez-Ribas, A. (2008). The Impact Of Firm Participation In R&D Programmes On R&D Partnerships. *Research Policy, 37*(2), 240–257. Https://Doi.Org/10.1016/J.Respol.2007.11.002

Cainelli, G., De Marchi, V., & Grandinetti, R. (2020). Do Knowledge-Intensive Business Services Innovate Differently? *Economics Of Innovation And New Technology, 29*(1), 48–65. Https://Doi.Org/10.1080/10438599.2019.1585639

Capurro, R., Fiorentino, R., Garzella, S., & Giudici, A. (2022). Big Data Analytics In Innovation Processes: Which Forms Of Dynamic Capabilities Should Be Developed And How To Embrace Digitization? *European Journal Of Innovation Management*, *25*(6), 273–294. Https://Doi.Org/10.1108/EJIM-05-2021-0256

Cefis, E., Bartoloni, E., & Bonati, M. (2020). Show Me How To Live: Firms' Financial Conditions And Innovation During The Crisis. *Structural Change And Economic Dynamics*, *52*, 63–81. Https://Doi.Org/10.1016/J.Strueco.2019.10.001

Chaudhary, S., Kaur, P., Talwar, S., Islam, N., & Dhir, A. (2022). Way Off The Mark? Open Innovation Failures: Decoding What Really Matters To Chart The Future Course Of Action. *Journal Of Business Research*, *142*, 1010–1025. Https://Doi.Org/10.1016/J.Jbusres.2021.12.062

Chege, S. M., Wang, D., & Suntu, S. L. (2020). Impact Of Information Technology Innovation On Firm Performance In Kenya. *Information Technology For Development*, *26*(2), 316–345. Https://Doi.Org/10.1080/02681102.2019.1573717

Chesbrough, H. W. (2003). *Open Innovation: The New Imperative For Creating And Profiting From Technology*. Harvard Business Press.

Chou, C., Young, K.-P., & Chiu, Y.-J. (2016). Coupled Open Innovation And Innovation Performance Outcomes: Roles Of Absorptive Capacity. *Corporate Management Review*, *36*(1), 37–68.

Ciampi, F., Demi, S., Magrini, A., Marzi, G., & Papa, A. (2021). Exploring The Impact Of Big Data Analytics Capabilities On Business Model Innovation: The Mediating Role Of Entrepreneurial Orientation. *Journal Of Business Research*, *123*, 1–13. Https://Doi.Org/10.1016/J.Jbusres.2020.09.023

Cockburn, I., Henderson, R., & Stern, S. (2019). The Impact Of Artificial Intelligence On Innovation: An Exploratory Analysis. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), *The Economics Of Artificial Intelligence: An Agenda* (Pp. 115–146). National Bureau Of Economic Research.

Cohen, W., & Levinthal, D. (1990). Absorptive Capacity: A New Perspective On Learning And Innovation. *Administrative Science Quarterly*, *35*(1), 128–152. Https://Doi.Org/10.2307/2393553

Colombelli, A., Krafft, J., & Vivarelli, M. (2016). To Be Born Is Not Enough: The Key Role Of Innovative Start-Ups. *Small Business Economics*, *47*(2), 277–291. Https://Doi.Org/10.1007/S11187-016-9716-Y

Dahiya, R., Le, S., Ring, J. K., & Watson, K. (2021). Big Data Analytics And Competitive Advantage: The Strategic Role Of Firm-Specific Knowledge. *Journal Of Strategy And Management*, *15*(2), 175–193. Https://Doi.Org/10.1108/JSMA-08-2020-0203

Davenport, T. (2014). *Big Data At Work: Dispelling The Myths, Uncovering The Opportunities*. Harvard Business Review Press. Https://Hbr.Org/2014/03/Big-Data-At-Work-Dispelling-The-Myths-Uncovering-The-Opportunities

Davies, R. (2015). *Industry 4.0: Digitalisation For Productivity And Growth*. European Parliamentary Research Service. Https://Www.Europarl.Europa.Eu/Regdata/Etudes/BRIE/2015/568337/EPRS_BRI(2015)568337_EN.Pdf

Douglas, D., & Radicic, D. (2022). Network Additionality And Policy Mix Of Regional And National Public Support For Innovation. *Economics Of Innovation And New Technology*, *31*(3), 148–172. Https://Doi.Org/10.1080/10438599.2020.1789277

Duan, Y., Cao, G., & Edwards, J. S. (2020). Understanding The Impact Of Business Analytics On Innovation. *European Journal Of Operational Research*, *281*(3), 673–686. Https://Doi.Org/10.1016/J.Ejor.2018.06.021

Ebersberger, B., Galia, F., Laursen, K., & Salter, A. (2021). Inbound Open Innovation And Innovation Performance: A Robustness Study. *Research Policy*, *50*(7), Article 104271. Https://Doi.Org/10.1016/J.Respol.2021.104271

Enkel, E., Bogers, M., & Chesbrough, H. (2020). Exploring Open Innovation In The Digital Age: A Maturity Model And Future Research Directions. *R&D Management*, *50*(1), 161–168. Https://Doi.Org/10.1111/Radm.12397

Enkel, E., Gassmann, O., & Chesbrough, H. (2009). Open R&D And Open Innovation: Exploring The Phenomenon. *R&D Management*, *39*(4), 311–316. Https://Doi.Org/10.1111/J.1467-9310.2009.00570.X

Ferraris, A., Bogers, M. L. A. M., & Bresciani, S. (2020). Subsidiary Innovation Performance: Balancing External Knowledge Sources And Internal Embeddedness. *Journal Of International Management*, *26*(4), Article 100794. Https://Doi.Org/10.1016/J.Intman.2020.100794

Frank, A. G., Dalenogare, L. S., & Ayala, N. F. (2019). Industry 4.0 Technologies: Implementation Patterns In Manufacturing Companies. *International Journal Of Production Economics*, *210*, 15–26. Https://Doi.Org/10.1016/J.Ijpe.2019.01.004

Frisk, J. E., & Bannister, F. (2017). Improving The Use Of Analytics And Big Data By Changing The Decision-Making Culture: A Design Approach. *Management Decision*, *55*(10), 2074–2088. Https://Doi.Org/10.1108/MD-07-2016-0460

Gaglio, C., Kraemer-Mbula, E., & Lorenz, E. (2022). The Effects Of Digital Transformation On Innovation And Productivity: Firm-Level Evidence Of South African Manufacturing Micro And Small Enterprises. *Technological Forecasting And Social Change*, *182*, Article 121785. Https://Doi.Org/10.1016/J.Techfore.2022.121785

Gao, H., Ding, X.-H., & Wu, S. (2022). Impact Of Knowledge Search On Product And Process Innovation: Mediating Role Of Absorptive Capacity And Moderating Role Of IT Capability. *European Journal Of Innovation Management*, *25*(2), 325–346. Https://Doi.Org/10.1108/EJIM-12-2019-0350

Gassmann, O., & Enkel, E. (2004, July 6–9). *Towards A Theory Of Open Innovation: Three Core Process Archetypes*. Proceedings Of The R&D Management Conference, Lisbon, Portugal.

Ghasemaghaei, M., & Calic, G. (2019). Does Big Data Enhance Firm Innovation Competency? The Mediating Role Of Data-Driven Insights. *Journal Of Business Research, 104*, 69–84. Https://Doi.Org/10.1016/J.Jbusres.2019.07.006

Ghasemaghaei, M., & Calic, G. (2020). Assessing The Impact Of Big Data On Firm Innovation Performance: Big Data Is Not Always Better Data. *Journal Of Business Research*, *108*, 147–162. Https://Doi.Org/10.1016/J.Jbusres.2019.09.062

Greco, M., Grimaldi, M., & Cricelli, L. (2019). Benefits And Costs Of Open Innovation: The Beco Framework. *Technology Analysis & Strategic Management*, *31*(1), 53–66. Https://Doi.Org/10.1080/09537325.2018.1484442

Griliches, Z. (1979). Issues In Assessing The Contribution Of R&D To Productivity Growth. *Bell Journal Of Economics*, *10*(1), 92–116. Https://Doi.Org/10.2307/3003321

Hervas-Oliver, J. L., Sempere-Ripoll, F., & Boronat-Moll, C. (2021). Technological Innovation Typologies And Open Innovation In Smes: Beyond Internal And External Sources Of Knowledge. *Technological Forecasting And Social Change*, *162*, Article 120338. Https://Doi.Org/10.1016/J.Techfore.2020.120338

Huber, G. P. (1991). Organizational Learning: The Contributing Processes And The Literatures. *Organization Science*, *2*(1), 88–115. Https://Doi.Org/10.1287/Orsc.2.1.88

Hullova, D., Trott, P., & Simms, C. D. (2016). Uncovering The Reciprocal Complementarity Between Product And Process Innovation. *Research Policy*, *45*(5), 929–940. Https://Doi.Org/10.1016/J.Respol.2016.01.012

Johnson, J. S., Friend, S. B., & Lee, H. S. (2017). Big Data Facilitation, Utilization, And Monetization: Exploring The 3Vs In A New Product Development Process. *Journal Of Product Innovation Management*, *34*(5), 640–658. Https://Doi.Org/10.1111/Jpim.12397

Jong, J. P. J. (2013). The Decision To Exploit Opportunities For Innovation: A Study Of High-Tech Small Business Owners. *Entrepreneurship Theory And Practice*, *37*(2), 281–301. Https://Doi.Org/10.1111/J.1540-6520.2011.00459.X

Kache, F., & Seuring, S. (2017). Challenges And Opportunities Of Digital Information At The Intersection Of Big Data Analytics And Supply Chain Management. *International Journal Of Operations & Production Management*, *37*(1), 10–36. Https://Doi.Org/10.1108/IJOPM-02-2015-0078

Kafetzopoulos, D., Gotzamani, K., & Gkana, V. (2015). Relationship Between Quality Management, Innovation And Competitiveness: Evidence From Greek Companies. *Journal Of Manufacturing Technology Management*, *26*(8), 1177–1200. Https://Doi.Org/10.1108/JMTM-02-2015-0007

Khanna, R., & Sharma, C. (2021). Do Technological Investments Promote Manufacturing Productivity? A Firm-Level Analysis For India. *Economic Modelling*, *105*, Article 105672. Https://Doi.Org/10.1016/J.Econmod.2021.105672

Kılıçaslan, Y., Sickles, R. C., Kayış, A. A., & Gürel, Y. Ü. (2017). Impact Of ICT On The Productivity Of The Firm: Evidence From Turkish Manufacturing. *Journal Of Productivity Analysis*, *47*(3), 277–289. Https://Doi.Org/10.1007/S11123-017-0497-3

Langley, D. J., Van Doorn, J., Ng, I. C. L., Stieglitz, S., Lazovik, A., & Boonstra, A. (2021). The Internet Of Everything: Smart Things And Their Impact On Business Models. *Journal Of Business Research*, *122*, 853–863. Https://Doi.Org/10.1016/J.Jbusres.2019.12.035

Laursen, K., & Salter, A. (2006). Open For Innovation: The Role Of Openness In Explaining Innovation Performance Among UK Manufacturing Firms. *Strategic Management Journal*, *27*(2), 131–150. Https://Doi.Org/10.1002/Smj.507

Lehrer, C., Wieneke, A., Vom Brocke, J., Jung, R., & Seidel, S. (2018). How Big Data Analytics Enables Service Innovation: Materiality, Affordance, And The Individualization Of Service. *Journal Of Management Information Systems*, *35*(2), 424–460. Https://Doi.Org/10.1080/07421222.2018.1451953

Leiponen, A. (2005). Organization Of Knowledge And Innovation: The Case Of Finnish Business Services. *Industry And Innovation*, *12*(2), 185–203. Https://Doi.Org/10.1080/13662710500087925

Leiponen, A. (2012). The Benefits Of R&D And Breadth In Innovation Strategies: A Comparison Of Finnish Service And Manufacturing Firms. *Industrial And Corporate Change*, *21*(5), 1255–1281. Https://Doi.Org/10.1093/Icc/Dts022

Liu, J., Chang, H., Forrest, J. Y.-L., & Yang, B. (2020). Influence Of Artificial Intelligence On Technological Innovation: Evidence From The Panel Data Of China's Manufacturing Sectors. *Technological Forecasting And Social Change*, *158*, Article 120142. Https://Doi.Org/10.1016/J.Techfore.2020.120142

Lorenz, R., Benninghaus, C., Friedli, T., & Netland, T. H. (2020). Digitization Of Manufacturing: The Role Of External Search. *International Journal Of Operations & Production Management*, *40*(7–8), 1129–1152. Https://Doi.Org/10.1108/IJOPM-06-2019-0498

Lozada, N., Arias-Pérez, J., & Henao-García, E. A. (2023). Unveiling The Effects Of Big Data Analytics Capability On Innovation Capability Through Absorptive Capacity: Why More And Better Insights Matter. *Journal Of Enterprise Information Management*, *36*(2), 680–701. Https://Doi.Org/10.1108/JEIM-02-2021-0092

Mairesse, J., & Mohnen, P. (2004). The Importance Of R&D For Innovation: A Reassessment Using French Survey Data. *The Journal Of Technology Transfer*, *30*(1–2), 183–197. Https://Doi.Org/10.1007/S10961-004-4365-8

Mariani, M. M., & Borghi, M. (2023). Artificial Intelligence In Service Industries: Customers' Assessment Of Service Production And Resilient Service Operations. *International Journal Of Production Research*, *62*(15), 5400–5416. Https://Doi.Org/10.1080/00207543.2022.2160027

Mariani, M. M., Machado, I., & Nambisan, S. (2023). Types Of Innovation And Artificial Intelligence: A Systematic Quantitative Literature Review And Research Agenda. *Journal Of Business Research*, *155*, Article 113364. Https://Doi.Org/10.1016/J.Jbusres.2022.113364

Marsh, I. W., Rincon-Aznar, A., Vecchi, M., & Venturini, F. (2017). We See ICT Spillovers Everywhere But In The Econometric Evidence: A Reassessment. *Industrial And Corporate Change*, *26*(6), 1067–1088. Https://Doi.Org/10.1093/Icc/Dtx008

Matthias, O., Fouweather, I., Gregory, I., & Vernon, A. (2017). Making Sense Of Big Data—Can It Transform Operations Management? *International Journal Of Operations & Production Management*, *37*(1), 37–55. Https://Doi.Org/10.1108/IJOPM-02-2015-0084

Mazzola, E., Bruccoleri, M., & Perrone, G. (2012). The Effect Of Inbound, Outbound And Coupled Innovation On Performance. *International Journal Of Innovation Management*, *16*(6), Article 1240008. Https://Doi.Org/10.1142/S1363919612400087

Mikalef, P., & Krogstie, J. (2020). Examining The Interplay Between Big Data Analytics And Contextual Factors In Driving Process Innovation Capabilities. *European Journal Of Information Systems*, *29*(3), 260–287. Https://Doi.Org/10.1080/0960085X.2020.1740618

Mina, A., Bascavusoglu-Moreau, E., & Hughes, A. (2014). Open Service Innovation And The Firm's Search For External Knowledge. *Research Policy*, *43*(5), 853–866. Https://Doi.Org/10.1016/J.Respol.2013.07.004

Mubarak, M. F., & Petraite, M. (2020). Industry 4.0 Technologies, Digital Trust And Technological Orientation: What Matters In Open Innovation? *Technological Forecasting And Social Change*, *161*, Article 120332. Https://Doi.Org/10.1016/J.Techfore.2020.120332

Neumeyer, X., Santos, S. C., & Morris, M. H. (2021). Overcoming Barriers To Technology Adoption When Fostering Entrepreneurship Among The Poor: The Role Of Technology And Digital Literacy. *IEEE Transactions On Engineering Management*, *68*(6), 1605–1618. Https://Doi.Org/10.1109/TEM.2020.2989740

Niebel, T., Rasel, F., & Viete, S. (2019). BIG Data – BIG Gains? Understanding The Link Between Big Data Analytics And Innovation. *Economics Of Innovation And New Technology*, *28*(3), 296–316. Https://Doi.Org/10.1080/10438599.2018.1493075

Nogueira, M., Fernández-López, S., Calvo, N., & Rodeiro-Pazos, D. (2018). Firm Characteristics, Financial Variables And Types Of Innovation: Influence In Spanish Firms' Survival. *International Journal Of Entrepreneurship And Innovation Management*, *22*(1–2), 57–79. Https://Doi.Org/10.1504/IJEIM.2018.10010670

Öberg, C., & Alexander, A. T. (2019). The Openness Of Open Innovation In Ecosystems: Integrating Innovation And Management Literature On Knowledge Linkages. *Journal Of Innovation & Knowledge*, *4*(4), 211–218. Https://Doi.Org/10.1016/J.Jik.2017.10.005

OECD. (2005). *Oslo Manual: Guidelines For Collecting And Interpreting Innovation Data* (4th Ed.). OECD Publishing.

OECD. (2022). *OECD Reviews Of Innovation Policy: Germany 2022: Building Agility For Successful Transitions*. OECD Publishing. Https://Doi.Org/10.1787/50b32331-En

OECD/Eurostat. (2018). *Oslo Manual 2018: Guidelines For Collecting, Reporting And Using Data On Innovation* (4th Ed.). OECD Publishing & Eurostat. Https://Doi.Org/10.1787/9789264304604-En

Ooms, W., & Piepenbrink, R. (2020). Open Innovation For Wicked Problems: Using Proximity To Overcome Barriers. *California Management Review*, *63*(2), 62–100. Https://Doi.Org/10.1177/0008125620968636

Petruzzelli, A. M., Murgia, G., & Parmentola, A. (2021). How Can Open Innovation Support Smes In The Adoption Of Industry 4.0 Technologies? An Empirical Analysis. *R&D Management*, *52*(4), 615–632. Https://Doi.Org/10.1111/Radm.12507

Phuyal, S., Bista, D., & Bista, R. (2020). Challenges, Opportunities And Future Directions Of Smart Manufacturing: A State-Of-The-Art Review. *Sustainable Futures*, *2*, Article 100023. Https://Doi.Org/10.1016/J.Sftr.2020.100023

Piñeiro-Chousa, J., López-Cabarcos, M. A., Romero-Castro, N. M., & Pérez-Pico, A. M. (2020). Innovation, Entrepreneurship And Knowledge In The Business Scientific Field: Mapping The Research Front. *Journal Of Business Research*, *115*, 475–485. Https://Doi.Org/10.1016/J.Jbusres.2019.11.045

Podsakoff, P. M., & Organ, D. W. (1986). Self-Reports In Organizational Research: Problems And Prospects. *Journal Of Management*, *12*(4), 531–544. Https://Doi.Org/10.1177/014920638601200408

Podsakoff, P. M., Mackenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common Method Biases In Behavioral Research: A Critical Review Of The Literature And Recommended Remedies. *Journal Of Applied Psychology*, *88*(5), 879–903. Https://Doi.Org/10.1037/0021-9010.88.5.879

Prause, G. (2015). Sustainable Business Models And Structures For Industry 4.0. *Journal Of Security And Sustainability Issues*, *5*(2), 159–169. Https://Doi.Org/10.9770/Jssi.2015.5.2(3)

Radicic, D. (2020). National And International R&D Support Programmes And Technology Scouting In European Small And Medium Enterprises (Smes). *Journal Of Science And Technology Policy Management*, *11*(4), 455–482. Https://Doi.Org/10.1108/JSTPM-10-2019-0091

Radicic, D. (2021). Breadth Of External Knowledge Search In Service Sectors. *Business Process Management Journal*, *27*(1), 230–252. Https://Doi.Org/10.1108/BPMJ-01-2020-0018

Radicic, D., & Alkaraan, F. (2022). Relative Effectiveness Of Open Innovation Strategies In Single And Complex SME Innovators. *Technology Analysis & Strategic Management*, *36*(9), 2113–2126. Https://Doi.Org/10.1080/09537325.2022.2130042

Radicic, D., & Petković, S. (2023). Impact Of Digitalization On Technological Innovations In Small And Medium-Sized Enterprises (Smes). *Technological Forecasting And Social Change*, *191*, Article 122474. Https://Doi.Org/10.1016/J.Techfore.2023.122474

Radicic, D., Douglas, D., Pugh, G., & Jackson, I. (2019). Cooperation For Innovation And Its Impact On Technological And Non-Technological Innovations: Empirical Evidence For European Smes In Traditional Manufacturing Industries. *International Journal Of Innovation Management*, *23*(5), Article 1950046. Https://Doi.Org/10.1142/S1363919619500464

Rammer, C., Czarnitzki, D., & Spielkamp, A. (2009). Innovation Success Of Non-R&D-Performers: Substituting Technology By Management In Smes. *Small Business Economics*, *33*(1), 35–58. Https://Doi.Org/10.1007/S11187-009-9185-7

Rammer, C., Fernandez, G. P., & Czarnitzki, D. (2022). Artificial Intelligence And Industrial Innovation: Evidence From German Firm-Level Data. *Research Policy*, *51*(7), Article 104555. Https://Doi.Org/10.1016/J.Respol.2022.104555

Ratten, V. (2015). International Consumer Attitudes Toward Cloud Computing: A Social Cognitive Theory And Technology Acceptance Model Perspective. *Thunderbird International Business Review*, *57*(3), 217–228. Https://Doi.Org/10.1002/Tie.21692

Reichstein, T., & Salter, A. (2006). Investigating The Sources Of Process Innovation Among UK Manufacturing Firms. *Industrial And Corporate Change*, *15*(4), 653–682. Https://Doi.Org/10.1093/Icc/Dtl014

Rüßmann, M., Lorenz, M., Gerbert, P., Waldner, M., Justus, J., Engel, P., & Harnisch, M. (2015). *Industry 4.0: The Future Of Productivity And Growth In Manufacturing Industries*. Boston Consulting Group.

Salampasis, D., & Mention, A. L. (2019). From Value Creation To Value Multiplication: Leveraging Outbound Open Innovation Practices For Unrelated Diversification In The Sensor Industry. *Technology Analysis & Strategic Management*, *31*(11), 1327–1340. Https://Doi.Org/10.1080/09537325.2019.1613520

Sarbu, M. (2021). The Impact Of Industry 4.0 On Innovation Performance: Insights From German Manufacturing And Service Firms. *Technovation*, *113*, Article 102415. Https://Doi.Org/10.1016/J.Technovation.2021.102415

Schumacher, A., Erol, S., & Sihn, W. (2016). A Maturity Model For Assessing Industry 4.0 Readiness And Maturity Of Manufacturing Enterprises. Procedia CIRP, 52, 161–166. Https://Doi.Org/10.1016/J.Procir.2016.07.040

Slater, S. F., Mohr, J. J., & Sengupta, S. (2014). Radical Product Innovation Capability: Literature Review, Synthesis, And Illustrative Research Propositions. Journal Of Product Innovation Management, 31(3), 552–566. Https://Doi.Org/10.1111/Jpim.12113

Solberg, E., Traavik, L. E. M., & Wong, S. I. (2020). Digital Mindsets: Recognizing And Leveraging Individual Beliefs For Digital Transformation. California Management Review, 62(4), 105–124. Https://Doi.Org/10.1177/0008125620931839

Sung, T. K. (2018). Industry 4.0: A Korea Perspective. Technological Forecasting And Social Change, 132, 40–45. Https://Doi.Org/10.1016/J.Techfore.2017.11.005

Tao, F., Qi, Q., Liu, A., & Kusiak, A. (2018). Data-Driven Smart Manufacturing. Journal Of Manufacturing Systems, 48, 157–169. Https://Doi.Org/10.1016/J.Jmsy.2018.01.006

Tehseen, S., Ramayah, T., & Sajilan, S. (2017). Testing And Controlling For Common Method Variance: A Review Of Available Methods. Journal Of Management Sciences, 4(2), 142–168. Https://Doi.Org/10.20547/Jms.2014.1704202

Teixeira, J. E., & Tavares-Lehmann, A. T. C. P. (2022). Industry 4.0 In The European Union: Policies And National Strategies. Technological Forecasting And Social Change, 180, Article 121664. Https://Doi.Org/10.1016/J.Techfore.2022.121664

Terjesen, S., & Patel, P. C. (2017). In Search Of Process Innovations: The Role Of Search Depth, Search Breadth, And The Industry Environment. Journal Of Management, 43(5), 1421–1446. Https://Doi.Org/10.1177/0149206315575710

Torres, P., & Augusto, M. (2019). Understanding Complementarities Among Different Forms Of Innovation. European Journal Of Innovation Management, 23(5), 813–834. Https://Doi.Org/10.1108/EJIM-01-2019-0012

Urbinati, A., Bogers, M., Chiesa, V., & Frattini, F. (2019). Creating And Capturing Value From Big Data: A Multiple-Case Study Analysis Of Provider Companies. Technovation, 84–85, 21–36. Https://Doi.Org/10.1016/J.Technovation.2018.07.004

Vidgen, R. T. (2020). Creating Business Value From Big Data And Business Analytics: Organizational, Managerial And Human Resource Implications. NEMODE Report.

Visnjic, I., Wiengarten, F., & Neely, A. (2016). Only The Brave: Product Innovation, Service Business Model Innovation, And Their Impact On Performance. Journal Of Product Innovation Management, 33(1), 36–52. Https://Doi.Org/10.1111/Jpim.12254

Von Krogh, G., Netland, T. H., & Wörter, M. (2018). Winning With Open Process Innovation. MIT Sloan Management Review, 59(2), 53–56.

Wang, Y., & Hajli, N. (2017). Exploring The Path To Big Data Analytics Success In Healthcare. Journal Of Business Research, 70, 287–299. Https://Doi.Org/10.1016/J.Jbusres.2016.08.002

Weissenberger-Eibl, M. A., & Hampel, T. (2021). Bridging The Gap: Integrating External Knowledge From Open Innovation Platforms. SN Business & Economics, 1(98), 1–32. Https://Doi.Org/10.1007/S43546-021-00101-5

Wen, X., Wu, G., Kang, Q., Wang, L., & Zeng, J. (2020). A Study On Customer Knowledge Management, Inbound Open Innovation And Firm Performance. Human Systems Management, 39(2), 183–195. Https://Doi.Org/10.3233/HSM-190720

West, J., & Bogers, M. (2014). Leveraging External Sources Of Innovation: A Review Of Research On Open Innovation. Journal Of Product Innovation Management, 31(4), 814–831. Https://Doi.Org/10.1111/Jpim.12125

Wilkinson, J. T., & Thomas, R. A. (2014). Innovation's Second Step. Thunderbird International Business Review, 56(3), 273–284. Https://Doi.Org/10.1002/Tie.21621

Wong, P. K., & He, Z. L. (2005). A Comparative Study Of Innovation Behaviour In Singapore's KIBS And Manufacturing Firms. Service Industries Journal, 25(1), 23–42. Https://Doi.Org/10.1080/0264206042000302397

World Economic Forum. (2018). The Future Of Jobs Report 2018. World Economic Forum.

Wünderlich, N. V., Heinonen, K., Ostrom, A. L., Patricio, L., Sousa, R., Voss, C., & Lemmink, J. G. A. M. (2015). Futurizing Smart Service: Implications For Service Researchers And Managers. Journal Of Service Management, 26(3), 442–447. Https://Doi.Org/10.1108/JOSM-01-2015-0040

Xu, L. D., Xu, E. L., & Li, L. (2018). Industry 4.0: State Of The Art And Future Trends. International Journal Of Production Research, 56(8), 2941–2962. Https://Doi.Org/10.1080/00207543.2018.1444806

Yun, J. J., Liu, Z., & Zhao, X. (2021). Introduction: Ambidextrous Open Innovation In The Fourth Industrial Revolution. Science, Technology And Society, 26(2), 183–200. Https://Doi.Org/10.1177/09717218211006969

Zangiacomi, A., Pessot, E., Fornasiero, R., Bertetti, M., & Sacco, M. (2020). Moving Towards Digitalization: A Multiple Case Study In Manufacturing. Production Planning & Control, 31(2–3), 143–157. Https://Doi.Org/10.1080/09537287.2019.1631468

Zeng, H., Ran, H., Zhou, Q., Jin, Y., & Cheng, X. (2022). The Financial Effect Of Firm Digitalization: Evidence From China. Technological Forecasting And Social Change, 183, Article 121951. Https://Doi.Org/10.1016/J.Techfore.2022.121951

Zhao, J. (2021). The Relationship Between Coupled Open Innovation And Innovation Performance: The Moderating Effect Of Platform Openness. Technology Analysis & Strategic Management, 35(2), 137–152. Https://Doi.Org/10.1080/09537325.2021.1970129

Zhou, D., Kautonen, M., Dai, W., & Zhang, H. (2021). Exploring How Digitalization Influences Incumbents In Financial Services: The Role Of Entrepreneurial Orientation, Firm Assets, And Organizational Legitimacy. Technological Forecasting And Social Change, 173, Article 121120. Https://Doi.Org/10.1016/J.Techfore.2021.121120