İktisat Politikası Araştırmaları Dergisi
Journal of Economic Policy Researches,
JEPR 2026, 13 (1): 292–308

https://doi.org/10.26650/JEPR1818833

Submitted 06.11.2025
Revision Requested 08.12.2025
Last Revision Received 21.01.2026
Accepted 22.01.2026

İktisat Politikası Araştırmaları Dergisi
Journal of Economic Policy Researches

Research Article

Open Access

Do All Roads Lead to Innovation? Unpacking the Effects of Digital Technologies on Innovation Types

Özlem Fikirli [1] & Hasan Şahin [2]

[1] Bartın University, Faculty of Economics and Administrative Sciences, Department of Economics, Bartın, Türkiye
[2] Ankara University, Faculty of Political Science, Department of Economics, Ankara, Türkiye

Abstract The digital transformation of economies has taken on a new dimension with the transition from traditional technologies to advanced technologies, such as artificial intelligence and big data analytics. This study examines the relationship between firms' adoption of advanced digital technologies—namely, AI, cloud computing, big data analytics, robotics, smart devices, and blockchain—and innovation, which are classified into six subcategories: product, process, organisational, marketing, ecological, and other innovations. The main contribution of this study is its comprehensive evaluation of the transition to advanced digital technologies, carefully considering the different innovation subcategories. In this study, the dataset from the Flash Eurobarometer 486 survey is analysed using a multivariate probit model, which allows simultaneous estimation while accounting for potential correlations among different types of innovation. According to the study findings, while advanced digital technologies generally support innovation, their effects vary significantly across innovation types. Cloud computing, big data analytics, and smart devices are emerging technologies with strong, widespread effects across all innovation categories. Artificial intelligence particularly supports product, process, and organisational innovations, whereas robotics technologies are more strongly associated with production-related and ecological innovations. In contrast, the impact of blockchain technology is more limited, primarily in organisational and marketing innovations. Overall, the results show that advanced digital technologies do not affect innovation processes uniformly; rather, each technology plays a distinct role depending on the nature of innovation. These findings suggest that firms should align their digital technology investments with their strategic innovation objectives and underscore the importance of policymakers designing digital transformation policies that are sensitive to different types of innovation.

Keywords Ecological innovation · Product innovation · Big data analytics · Artificial intelligence · Robotics

JEL Classification D22 · O12 · O33

Author Note This study is derived from the doctoral dissertation 'Three Essays on Sustainable Growth,' prepared in the Department of Economics at Ankara University, Graduate School of Social Sciences.

Citation: Fikirli, Ö. & Şahin, H. (2026). Do all roads lead to innovation? Unpacking the effects of digital technologies on innovation types. *İktisat Politikası Araştırmaları Dergisi–Journal of Economic Policy Researches*, *13*(1), 292-308. https://doi.org/10.26650/JEPR1818833

This work is licensed under Creative Commons Attribution-NonCommercial 4.0 International License.

2026. Fikirli, Ö. & Şahin, H.

Corresponding author: Özlem Fikirli ozlem_fikirli@hotmail.com

Do All Roads Lead to Innovation? Unpacking the Effects of Digital Technologies on Innovation Types

The concept of sustainable growth underscores the pivotal role of innovation as a fundamental driver in endogenous growth models. This recognition has firmly established the significance of innovation in the economic literature, aligning with the widespread consensus on its critical importance. However, despite the clarity surrounding the importance of innovation, uncertainties persist regarding the nature and classification of its various types. Innovation can be categorised in numerous ways, including technological versus non-technological, radical versus incremental, and social innovation. The Oslo Manual, developed by the OECD and Eurostat, classifies innovation into four main types: product, process, marketing, and organisational innovation (OECD, 2005). Moreover, newer concepts, such as social (Adams & Hess, 2010) and ecological innovation (Rennings, 2000), can also be integrated into this framework. By grouping innovations outside these established categories as others, innovation can be classified into seven distinct categories: product, process, marketing, organisational, social, ecological, and others.

The process that has emerged from developments in computer technologies, such as "Industry 4.0," "Fourth Industrial Revolution," or "Digital Age," reflects the digital transformation of economies (Maresova et al., 2018; Tirole, 2023). This transformation, which can be considered a driving force behind evolutionary impacts in technology, also leads to significant changes in technology-driven innovation. This shift creates substantial differences in innovation, including its emergence process, characteristics, and market impact. Given the unique features of different types of innovation, it is reasonable to expect that the effects of this transformation will also vary. Can different digital technologies genuinely have the same impact on various types of innovation?

The digital transformation process entails changes in consumer and firm behaviour, as well as the transformation of micro- and macro-level economic phenomena, reshaping market structures (Sagar, 2024; Zhao et al., 2025). A country's competitive power in these evolving market structures depends on its ability to sustain digital transformation. An essential factor in completing the digital transformation process is the firm. Firms must continue to adopt digital technologies to maintain their competitiveness. Adopting digital technologies is crucial for maintaining a competitive edge and ensuring the efficient use of firm resources. Moreover, it plays a crucial role in emerging global firms in markets.

Another significant result of the digital transformation process in firms is the facilitation of firm growth. Digitalisation leads to an increase in firm performance and growth effects (Müller et al., 2018; DeStefano et al., 2020) through various channels, such as reducing information asymmetries (Kong et al., 2022), strengthening the supply chain (Büyüközkan & Göçer, 2018), reducing transaction costs (Kimani et al., 2020), and increasing efficiency (Ballestar et al., 2020). Furthermore, adopting digital technologies plays a crucial role in firms' innovation activities and contributes to firm growth through this channel (Ferreira et al., 2019:588).

Developments in digital technologies, particularly in the 21st century, have led to the emergence of advanced digital technologies, also known as Industry 4.0 technologies. These include robotics, blockchain, artificial intelligence, and more. The scope of this study is limited to advanced digital technologies, including artificial intelligence, cloud computing, big data analytics, robotics, smart devices, and blockchain. The primary constraint in defining the scope of this study is the availability of accessible datasets; therefore, the research is restricted to exploring the role of advanced digital technologies in various types of innovation.

While the application areas and purposes of advanced digital technologies sometimes overlap, they also diverge. For example, cloud computing and big data analytics, widely used in firms' marketing departments,

may appear similar in their applications, but their purposes differ. Cloud computing primarily facilitates data storage, whereas big data analytics helps evaluate marketing strategies and support decision-making. The unique characteristics of these technologies also contribute to differences in their impacts on innovation. Moreover, given the structural differences among types of innovation, it is unlikely that advanced digital technologies will have similar effects across them. The main argument of the study is that the impact of advanced digital technologies on innovation varies by innovation type. Given that firms primarily seek to maximise profits, this study classifies innovation into six subcategories: product, process, marketing, organisational, ecological, and other innovations.

Although the transition to advanced digital technologies continues to accelerate, the number of studies examining their economic impacts remains limited. Furthermore, few studies examine the role of advanced digital technologies in innovation. Existing research tends to focus on a single advanced digital technology (Kshetri, 2011; Niebel et al., 2019; Ghasemaghaei & Calic, 2020; Rammer et al., 2021) and often does not categorise different types of innovation (Niebel et al., 2019; Ghasemaghaei & Calic, 2020). However, these studies are among the first to highlight the positive impact of advanced digital technologies on innovation (Kshetri, 2011; Niebel et al., 2019; Ghasemaghaei & Calic, 2020; Rammer et al., 2021). This study conducts a comprehensive analysis that accounts for the unique nature of advanced digital technologies and the various types of innovation. This approach establishes a robust framework for developing policy recommendations that strategically align advanced digital technologies with the distinct types of innovation being pursued.

This study aims to determine the relationship between firms' adoption of advanced digital technologies and their innovation activities. The second section discusses the effects of digital technologies on firms and the importance of collaboration within an organisation. The third section presents the data and the method used in the study. The next section presents the research findings. Finally, the last section discusses the results and conclusions.

Related Literature

Developments in computer and information technologies that emerged in the late 20th century have transformed the entire economic structure. This progress has taken on a new dimension in the 21st century, evolving into more advanced technologies, such as artificial intelligence and cloud computing. Advanced digital technologies reveal significant changes in the fundamental elements of the economic structure, from consumer behaviour to the supply chain. It is believed that digitalisation can help address the stagnation that has emerged recently in developing markets (Van Ark, 2015; Remes et al., 2018).

Economic development is a multifaceted process that extends beyond mere economic growth, incorporating structural advancements in key social sectors such as healthcare and education. In this context, advanced digital technologies are pivotal, aligning with sustainability goals to further propel development. These technologies have shown increasing influence through innovations in resource and energy efficiency, waste management, environmental impact reduction, and the integration of smart city solutions (World Economic Forum, 2017; OECD, 2019).

Moreover, the implementation of advanced digital technologies has significantly enhanced public service delivery, particularly in healthcare and education. For instance, in healthcare, artificial intelligence (AI) supports early disease detection and drug discovery, enabling faster, more accurate medical interventions. In education, big data analytics enables the creation of personalised learning systems that tailor educational experiences to individual needs, thereby improving learning outcomes.

The positive effects of digital technologies, particularly in knowledge economies, have strengthened the link between digitalisation and innovation (Ciarli et al., 2021; Kastelli et al., 2024; Zhang et al., 2024). A key argument in innovation theories is that knowledge accumulation accelerates the innovation process. Digital technologies, primarily through internet-based applications, enable faster access to new knowledge and significantly lower the costs of acquiring information. Easier access to other institutions and organisations, along with reduced costs, creates knowledge externalities, leading to rapid knowledge accumulation. As a result, the production of new knowledge increases, fostering the widespread diffusion of innovation. Additionally, more refined and faster market analyses, enabled by digital technologies, increase the likelihood of success in innovation efforts. Furthermore, advanced digital technologies reduce prototyping costs, supporting the efficient development of product innovations. Moreover, digital technologies accelerate ecological innovation by delivering environmental benefits, such as enhanced energy efficiency.

One of the key elements in determining the relationship between digitisation and growth is the firm, the backbone of the economy. The effects of adopting digital technologies on firms have been the focus of researchers in related literature. The impact of adopting digital technologies on firms has been investigated from various aspects, including growth (DeStefano et al., 2020), performance (Ferraris et al., 2019), innovation (Rammer et al., 2021), and productivity (Müller et al., 2018; Heyman et al., 2021). It has been suggested that adopting digital technologies will have a positive effect on the factors examined in these studies.

Among the impacts of digital technologies on firms, innovation become prominent, primarily by providing a competitive advantage and supporting growth. Digital technologies alter firms' organisational and infrastructural characteristics, transforming innovation activities (Nambisan et al., 2019). Moreover, in addition to changing the information production process, which is at the core of innovation (Antonelli, 2017), digital technologies also increase the stock of information as an input in the production process (Léger & Swaminathan, 2007). Furthermore, adopting digital technologies in firms supports innovation through various channels, such as increased efficiency, improved information quality through data extraction methods, facilitated information management and decision-making, and reduced information access costs.

Limited studies in the literature examine the relationship between advanced digital technologies and firms' innovation activities. In these studies, the impact of technologies such as artificial intelligence (Rammer et al., 2021), cloud computing (Kshetri, 2011), and big data analytics (Niebel et al., 2019; Ghasemaghaei & Calic, 2020) on innovation has been examined. To the best of our knowledge, no study has investigated the relationship between advanced digital technologies and innovation, categorised innovation types, or comprehensively analysed the various types of advanced digital technologies. However, the relative novelty of advanced digital technologies and potential delays in adoption may explain the limited literature in this area. Therefore, the effects of advanced digital technologies on firm innovation activities remain poorly understood.

Prior research's tendency to focus on specific types of innovation has often produced binary outcomes for the variables studied. Consequently, methods such as the probit model have been frequently employed (Niebel et al., 2019; Rammer et al., 2021), although structural equation modelling (Ghasemaghaei & Calic, 2020), ordinary least squares (Rammer et al., 2021), and Heckman selection (Niebel et al., 2019) have also been used.

It would be an overly broad assumption to expect advanced digital technologies to play the same role across different types of innovation. Innovation types often have significant structural differences that can influence the relevance and prominence of specific technologies. Depending on the kind of innovation, certain advanced digital technologies may take precedence.

The literature raises the question of whether advanced digital technologies have heterogeneous effects across innovation types. Furthermore, it seeks to determine which advanced digital technologies are prioritised for specific kinds of innovation.

Regardless of its type, a central concept in innovation theories is the role of knowledge as the foundation of innovation. The diffusion of knowledge is the process by which knowledge spreads among economic actors. This diffusion plays a crucial role in innovation by enabling interactions with the international market through globalisation and collaboration with other institutions. Firms acquire knowledge from national and global markets through globalisation and collaboration channels, thereby reducing knowledge asymmetries. This enables firms to gather more information about new technologies and stay abreast of market transformations.

The globalisation of firms is often characterised by export activities (Hsu et al., 2006; Arvanitis et al., 2017). Firms engaged in exports tend to have greater awareness of new technologies, as they are more likely to be integrated into global markets. Specifically, in the context of digital technologies, adopting new technologies offers advantages such as reducing transaction costs in global markets and enabling rapid responses to market developments. Beyond these advantages, the intensified competitive environment also compels firms to adopt new technologies to maintain their global market positions.

In the new institutional economics approach, the concept of rational behaviour has evolved into the notion of "rules of the game" that shape interactions among economic actors (North, 1990:3). These rules include laws and regulations, traditional organisational structures, and social norms (DiMaggio, 1998). Access to other market actors and the collaborative environment are also significant factors that shape the rules of the game. Improvements in the market's collaborative structure, where firms operate, will enhance the creation of shared value, thereby increasing firms' competitiveness and supporting innovation.

Data and Methods

The study uses data from the "SMEs, Start-ups, Scale-ups, and Entrepreneurship" Flash Eurobarometer survey, conducted by the European Commission (European Commission, 2020). The survey covers 27 European Union (EU) countries, Bosnia and Herzegovina, Brazil, Canada, Iceland, Japan, North Macedonia, Norway, Serbia, Turkiye, the United Kingdom, the United States, and Kosovo. It is administered to micro-enterprises (60% of the sample), small enterprises (20% of the sample, with a minimum of 30 firms), medium-sized enterprises (15% of the sample, with a minimum of 20 firms), and large enterprises (5% of the sample, with a minimum of 10 firms) in all countries. To ensure representation across sectors, firms are selected from different industries, including manufacturing (NACE category C), retail (NACE category G), services (NACE categories H, I, J, K, L, M, N, P, Q, and R), and industry (NACE categories B, D, E, and F). The number of firms surveyed in each sector is determined by the proportion of firms in that sector in each country (European Commission, 2020).

The survey used in this study targeted firms in a specific region. Accordingly, the study is constrained by the dataset of firms from these geographical areas. A significant portion of the sample consists of firms located in EU countries. Given the EU's Digital Single Market strategy, the selected sample is probably relatively homogeneous. However, the survey design does not support a longitudinal analysis of the impact of advanced digital technologies. Nevertheless, it offers significant insights into overarching trends and the effects of adopting these technologies.

This study investigates firm innovation activities in the context of knowledge diffusion. Among the elements representing knowledge diffusion, the research focuses primarily on the adoption of advanced digital technologies. In addition, the model includes channels noted in the literature as supporting knowl-

edge diffusion, such as international trade and participation in a global value chain (Léger & Swaminathan, 2007). Finally, variables identified in the applied innovation literature as determinants, including firm characteristics and the environment in which the firm operates, are added to the model (Sternberg & Arndt, 2001; Hobday, 2005; Léger & Swaminathan, 2007). Firm size, a determinant of innovation, is measured by the number of employees in this study. Environmental characteristics of firms are examined using proxy variables that capture the firm's location, the collaborative environment in its market, and the industry in which it operates.

Variables used to examine the relationship between the diffusion of digital technologies and innovation, along with their definitions, are listed in Table 1. In the table, the dependent variables indicate whether firms have implemented different types of innovation. The innovation categories considered include product, process, organisational, marketing, and eco-innovation, as well as other forms of innovation beyond these categories.

Table 1

Definition of variables

Variables	Definition
Dependent Variables	
ino_product	If the firm introduced product innovation during the past 12 months = 1, else = 0.
ino_process	If the firm introduced process innovation during the past 12 months = 1, else = 0.
ino_organizational	If the firm introduced organisational innovation during the past 12 months = 1, else = 0.
ino_marketing	If the firm introduced marketing innovation during the past 12 months = 1, else = 0.
ino_eco	If the firm introduced ecological innovation during the past 12 months = 1, else = 0.
ino_other	If the firm introduced other types of innovation during the past 12 months = 1, else = 0.
Independent Variables	
artificial intelligence	If the firm has adopted artificial intelligence =1, else = 0.
cloud computing	If the firm has adopted cloud computing =1, else = 0.
big data analytics	If the firm has adopted big data analytics =1, else = 0.
robotics	If the firm has adopted robotics =1, else = 0.
smart devices	If the firm has adopted smart devices =1, else = 0.
blockchain	If the firm has adopted blockchain =1, else = 0.
employment	Natural logarithm of the number of employees
location	If the company is in a large town or city = 1, otherwise = 0
globalisation	If the firm exported goods or services in 2019 = 1, else = 0.
international group	If the firm is part of the global value chain =1, else = 0.
collaboration	Access to and collaboration with business partners (other enterprises, the public sector, educational institutions, research organisations, etc.)
	Very good = 4, Fairly good = 3, Fairly poor = 2, Very poor = 1.
Sector Dummies	
services	If the firm is operated in services = 1, else = 0.
manufacturing	If the firm is operated in manufacturing = 1, else = 0.
retail	If the firm is operated in retail = 1, else = 0.

The independent variables include firm characteristics commonly regarded as key determinants of innovation, namely firm size, location, export activity, affiliation with an international business group, and market structure. The study's core focus, however, is on independent variables related to digital technolo-

gies. These digital technology variables indicate whether firms have integrated digital technologies into their operations.

The relative novelty of advanced digital technologies significantly limits the availability of accessible datasets. In addition to recent surveys evaluating the use of these technologies, tracking the same firms in micro-level surveys poses further challenges. These factors have been crucial in the use of cross-sectional data for this study. However, using cross-sectional data does not allow distinguishing the temporal effects of the transition to advanced digital technologies.

This study examines the role of firms' adoption of advanced digital technologies in innovation using a multivariate probit model. The multivariate probit model is an econometric technique that enables the simultaneous estimation of multiple equations, each with a binary dependent variable. It allows the simultaneous analysis of multiple binary-dependent variables influenced by common explanatory variables. It is also possible to simultaneously estimate binary-dependent variables affected by different explanatory variables (Cappellari & Jenkins, 2003:279).

The multivariate probit model accounts for the simultaneity and correlation among the estimated-dependent variables. In this study, the relationship between advanced digital technologies and various types of innovation is examined by estimating equations in which innovation types are treated as dependent variables. However, there are multiple types of innovation, and common determinants, such as firm strategy, managerial characteristics, and the quality of human capital, influence firms' approaches to innovation and the implementation of innovation. As such, rather than estimating innovation with independent equations, a multivariate probit model that accounts for error-term correlation is more appropriate. The findings also highlight the correlation among the error terms and underscore the necessity of simultaneous equation estimation.

The general representation of the multivariate probit model is given by Equations 1, 2, 3, and 4 (Cappellari & Jenkins, 2003:279; Greene, 2003:710). In the following equations, y_{ij}*, y_{ij}, x_{ij}, β_{ij}', and ε_{ij} denote the continuous unobservable variable, the observed counterpart of y_{ij}*, independent variables, coefficients, and the error term. The error term is assumed to follow a multivariate normal distribution with zero mean and common variance across equations. The covariances among the error terms are allowed to be nonzero. Therefore, the variance-covariance matrix of the error term has diagonal elements equal to one, and the off-diagonal elements are symmetric.

$$y_{ij}^{*} = \beta_j' x_{ij} + \varepsilon_{ij} \qquad j = 1, 2, ..., J \tag{1}$$

$$y_{ij} = \begin{cases} 1, & y_{ij}^{*} > 0 \\ 0, & \text{else} \end{cases} \tag{2}$$

$$E[\varepsilon_1 \mid x_1, x_2, ..., x_J] = E[\varepsilon_2 \mid x_1, x_2, ..., x_J] = ... = E[\varepsilon_J \mid x_1, x_2, ..., x_J] = 0 \tag{3}$$

$$\mathrm{Var}[\varepsilon_1 \mid x_1, x_2, ..., x_J] = \mathrm{Var}[\varepsilon_2 \mid x_1, x_2, ..., x_J] = ... = \mathrm{Var}[\varepsilon_J \mid x_1, x_2, ..., x_J] = 1 \tag{4}$$

In this study, the relationship between the adoption of advanced digital technologies and innovation activity, divided into six subcategories, is simultaneously predicted using common explanatory variables. The multivariate probit model is estimated using the simulated maximum likelihood method, with one of the most popular simulations used to approximate the multivariate normal distribution, namely the Geweke-Hajivassiliou-Keane (GHK) smooth recursive conditioning simulation procedure. The log-likelihood function of the six-variable standard normal distribution is shown in Equation 5. Φ_6 represents the six-variable standard normal distribution with mean E_i and variance-covariance matrix Ω, while wi represents

the optional weight in the equation (Cappellari & Jenkins, 2003:279-280). In this study, estimation results are obtained without weighting.

$$L = \sum_{i=1}^{N} w_i \log \Phi_6(E_i, \Omega) \tag{5}$$

$$E_i = (K_{i1}\beta_1' x_{i1}, K_{i2}\beta_2' x_{i2}, K_{i3}\beta_3' x_{i3}, K_{i4}\beta_4' x_{i4}, K_{i5}\beta_5' x_{i5}, K_{i6}\beta_6' x_{i6}) \tag{6}$$

$$K_{ij} = 2y_{ij} - 1 \tag{7}$$

$$\begin{gathered}\Omega_{jk} = \{(1, \text{if } j = k) \\ (\Omega_{kj} = K_{ij}K_{ik}\rho_{jk} = K_{ij}K_{ik}\rho_{kj}, \text{if } j \neq k)\}\end{gathered} \tag{8}$$

Correlation among decisions in the multivariate probit model can be assessed using the Lagrange multiplier test statistic, likelihood ratio test, or Wald test (Greene, 2003: 712). In all six cases examining the presence of correlation, the null hypothesis is that the covariance, ρ, equals zero. When the null hypothesis is accepted, the models consist of independently estimable equations because the error terms are uncorrelated. In other words, estimating a separate probit model for each equation is acceptable instead of using the multivariate probit model.

The study has 2^6 possible scenarios based on the probabilities of the observed variables, taking values of 0 and 1. If all outcomes are named as success when they have a value of 1 and failure when they have a value of 0, the probability of all outcomes being successful is as specified in the following equations (Cappellari & Jenkins, 2003:280).

$$\begin{gathered}\text{Prob}\ (y_1 = 1, y_2 = 1, y_3 = 1, y_4 = 1, y_5 = 1, y_6 = 1) = \text{Prob}\ (\varepsilon_1 \leq \beta_1' x_1, \varepsilon_2 \leq \beta_2' x_2, \varepsilon_3 \leq \beta_3' x_3, \varepsilon_4 \leq \beta_4' x_4, \\ \varepsilon_5 \leq \beta_5' x_5, \varepsilon_6 \leq \beta_6' x_6)\end{gathered} \tag{9}$$

$$\begin{gathered}\text{Prob}\ (y_1 = 1, y_2 = 1, y_3 = 1, y_4 = 1, y_5 = 1, y_6 = 1) = \text{Prob}\ (\varepsilon_6 \leq \beta_6' x_6 \mid \varepsilon_5 < \beta_5' x_5, \varepsilon_4 < \beta_4' x_4, \\ \varepsilon_3 < \beta_3' x_3, \varepsilon_2 < \beta_2' x_2, \varepsilon_1 < \beta_1' x_1) * \text{Prob}\ (\varepsilon_5 < \beta_5' x_5 \mid \varepsilon_4 < \beta_4' x_4, \varepsilon_3 < \beta_3' x_3, \varepsilon_2 < \beta_2' x_2, \varepsilon_1 < \beta_1' x_1) \\ * \text{Prob}\ (\varepsilon_4 < \beta_4' x_4 \mid \varepsilon_3 < \beta_3' x_3, \varepsilon_2 < \beta_2' x_2, \varepsilon_1 < \beta_1' x_1) * \text{Prob}\ (\varepsilon_3 < \beta_3' x_3 \mid \varepsilon_2 < \beta_2' x_2, \varepsilon_1 < \beta_1' x_1) \\ * \text{Prob}\ (\varepsilon_2 < \beta_2' x_2 \mid \varepsilon_1 < \beta_1' x_1) * \text{Prob}\ (\varepsilon_1 < \beta_1' x_1)\end{gathered} \tag{10}$$

The role of advanced digital technology adoption in firms' innovation activities is examined in the context of knowledge diffusion by estimating Equation 11. The equation includes the number of employees, location, globalisation, international group, and market collaboration structure, along with variables related to the adoption of advanced digital technologies. The terms y_i^*, ε_i, and β represent unobserved continuous variables, error terms, and unknown coefficients.

$$\begin{gathered}y_i^* = \beta_1 artificial\ intelligence_i + \beta_2 cloud\ computing_i + \beta_3 big\ data_i + \beta_4 robotics_i + \beta_5 smart\ devices_i \\ + \beta_6 block\ chain_i + \beta_7 employment_i + \beta_8 location_i + \beta_9 globalization_i + \beta_{10}\ international\ group_i + \\ \beta_{11} collaboration_i + \beta_{12} services_i + \beta_{13} manufacturing_i + \beta_{14} retail_i + \varepsilon_i\end{gathered} \tag{11}$$

The descriptive statistics for the variables used in the study are presented in Table 2. The mean values of the digital technology variables in Table 2 reflect the adoption rate of digital technologies among firms in the sample. According to Table 2, approximately 50% of firms have adopted cloud computing, making it the most widely adopted digital technology. Cloud computing is followed by smart devices (29%), big data analytics (16%), robotics (9%), artificial intelligence (8%), and blockchain (4%).

The widespread adoption of cloud computing can be attributed to the increasing volume and variety of data, which have driven growing data storage needs, as well as the relatively lower cost of cloud computing

compared with other digital technologies. The current data landscape has also contributed to big data analytics being ranked as the third most adopted digital technology.

By contrast, smart devices and robotics—often associated with automating production processes—rank second and fourth, respectively. In contrast, artificial intelligence and blockchain, which are relatively newer technologies compared with the others, have the lowest adoption rates. The novelty of these technologies may also limit firms' awareness of their potential applications.

Table 2

Descriptive Statistics

Variables	Mean	Standard Deviation	Minimum	Maximum
ino_product	0.293	0.455	0	1
ino_process	0.210	0.407	0	1
ino_organizational	0.172	0.378	0	1
ino_marketing	0.221	0.415	0	1
ino_eco	0.232	0.422	0	1
ino_other	0.085	0.279	0	1
artificial intelligence	0.083	0.276	0	1
cloud computing	0.498	0.500	0	1
big data analytics	0.157	0.364	0	1
robotics	0.092	0.289	0	1
smart devices	0.294	0.455	0	1
blockchain	0.036	0.186	0	1
employment	2.421	1.641	0	9.200
location	0.500	0.500	0	1
globalisation	0.343	0.475	0	1
international group	0.101	0.301	0	1
collaboration	2.980	0.705	1	4
services	0.405	0.491	0	1
manufacturing	0.201	0.401	0	1
retail	0.272	0.445	0	1
Observations: 13042				

Results

The results of the multivariate probit estimation are presented in Table 3. The likelihood ratio test evaluates whether the models should be estimated simultaneously. Based on the p-value and chi-square value, the null hypothesis is rejected. Therefore, the multivariate probit model, which accounts for correlations among variables, is necessary rather than estimating the dependent variables separately in independent models. All correlation coefficients are significant at least 5%, and the coefficients are positive. In other words, there is a positive, significant correlation among the error terms across all models. Firm innovation activities are closely related to their characteristics, goals, and policies, ranging from financial situation to employee quality. Therefore, a relationship is expected between different types of innovation when a firm engages in multiple innovation.

According to the estimation results, export activities and participation in the global value chain have a significant, at least 5% level, and positive relationship with all innovation activities. There is a significant

relationship at the 1% level between the number of employees and all types of innovation, except product and other innovation. The direction of the relationship is negative for marketing innovation, whereas it is positive for all other kinds of innovation. Furthermore, at least at the 1% level, there is a significant positive relationship between the firm's location and marketing innovation. In comparison, there is a significant negative relationship with eco-innovation at the 5% level. Finally, there is a significant, at least at the 5% level, positive relationship between the market's collaboration structure and product innovation and eco-innovation.

According to Table 3, at least at the 5% level, there is a significant positive relationship between the adoption of artificial intelligence technology and all types of innovation, except for other types of innovation. In addition, at least at the 5% level, there is a significant positive relationship between the adoption of cloud computing, big data analytics, smart devices, and all types of innovation. Moreover, the adoption of robotics technology is associated with a significant positive relationship, at least at the 5% level, with all types of innovation, except marketing and organisational innovation. Lastly, the adoption of blockchain technology is associated with a significant positive relationship with organisational and marketing innovation, at least at the 5% level.

Table 3

Multivariate Probit Estimation Results (Coefficients)

Independent Variables	**Dependent Variables**					
	ino_product	ino_process	ino_organizational	ino_marketing	ino_eco	ino_other
artificial intelligence	0.222*** (0.057)	0.167*** (0.050)	0.096** (0.046)	0.152*** (0.045)	0.116*** (0.042)	0.080 (0.067)
cloud computing	0.192*** (0.028)	0.125*** (0.029)	0.231*** (0.023)	0.198*** (0.028)	0.076*** (0.027)	0.107*** (0.037)
big data analytics	0.203*** (0.037)	0.168*** (0.035)	0.220*** (0.038)	0.245*** (0.043)	0.206*** (0.054)	0.107** (0.043)
robotics	0.164*** (0.040)	0.392*** (0.049)	0.084* (0.046)	−0.022 (0.053)	0.200*** (0.053)	0.177*** (0.062)
smart devices	0.248*** (0.026)	0.242*** (0.032)	0.121*** (0.034)	0.164*** (0.029)	0.469*** (0.033)	0.099*** (0.032)
blockchain	0.081 (0.051)	0.111 (0.070)	0.215*** (0.071)	0.132** (0.056)	0.095* (0.057)	0.152* (0.079)
employment	0.004 (0.008)	0.030*** (0.010)	0.071*** (0.011)	−0.023*** (0.009)	0.062*** (0.008)	0.013 (0.010)
location	0.043 (0.028)	−0.042 (0.027)	0.023 (0.026)	0.079*** (0.021)	−0.068** (0.028)	0.006 (0.036)
globalisation	0.293*** (0.025)	0.171*** (0.034)	0.145*** (0.034)	0.078** (0.037)	0.110*** (0.030)	0.124*** (0.040)
international group	0.222*** (0.048)	0.123** (0.050)	0.209*** (0.042)	0.123*** (0.047)	0.199*** (0.039)	0.189*** (0.038)
collaboration	0.058*** (0.019)	0.034 (0.021)	0.027 (0.018)	0.035 (0.022)	0.061** (0.028)	−0.020 (0.018)
services	0.177*** (0.049)	−0.081* (0.046)	0.088* (0.051)	0.229*** (0.045)	−0.088* (0.047)	0.090 (0.065)
manufacturing	0.405*** (0.057)	0.326*** (0.050)	−0.049 (0.055)	0.131*** (0.048)	−0.034 (0.054)	−0.015 (0.089)

Independent Variables	Dependent Variables					
	ino_product	ino_process	ino_organizational	ino_marketing	ino_eco	ino_other
retail	0.408*** (0.045)	−0.097 (0.060)	0.032 (0.046)	0.393*** (0.050)	−0.038 (0.044)	0.024 (0.075)
constant	−0.923*** (0.073)	−1.055*** (0.094)	−1.550*** (0.076)	−0.897*** (0.083)	−1.240*** (0.103)	−1.703*** (0.091)
	Correlation Coefficient			**Coefficient standard deviation**		
rho 21	0.303***			(0.022)		
rho 31	0.203***			(0.020)		
rho 41	0.324***			(0.021)		
rho 51	0.239***			(0.018)		
rho 61	0.099***			(0.025)		
rho 32	0.228***			(0.022)		
rho 42	0.235***			(0.023)		
rho 52	0.265***			(0.019)		
rho 62	0.114***			(0.031)		
rho 43	0.315***			(0.020)		
rho 53	0.154***			(0.020)		
rho 63	0.103***			(0.032)		
rho 54	0.199***			(0.021)		
rho 64	0.064**			(0.026)		
rho 65	0.079***			(0.027)		
Likelihood ratio test (H0: rho21 = rho31 = rho41 = rho51 = rho61 = rho32 = rho42 = rho52 = rho62 = rho43 = rho53 = rho63 = rho54 = rho64 = rho65 = 0)				Chi- (15) = 2042.23 Prob = 0.0000		

Values in parentheses are robust standard errors. Standard errors were obtained using the cluster property by country.*, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively. Country characteristics were considered. The reference sector is industry.

The marginal effects of digital technologies from multivariate probit estimation are presented in Table 4. According to the table, if firms adopt artificial intelligence technology, the probability of introducing product, process, organisational, marketing, and ecological innovation increases by 7%, 4%, 2%, 4%, and 3%. Furthermore, firms' adoption of cloud computing, big data analytics, or smart device technologies leads to increases in the implementation of product, process, organisational, marketing, ecological, and other types of innovation by 6%, 3%, 5%, 5%, 2%, 1%; 7%, 4%, 5%, 7%, 6%, 2%; and 8%, 6%, 3%, 5%, 14%, 1%, respectively. Next, with the adoption of robotics technology, the probability of applying product, process, ecological, and other innovation types increases by 5%, 11%, 6%, and 3%, respectively. Finally, if firms adopt blockchain technology, the probability of introducing organisational and marketing innovation increases by 5% and 4%, respectively.

Table 4

Marginal Effects of Digital Technologies

Independent Variables	Dependent Variables					
	ino_product	ino_process	ino_organizational	ino_marketing	ino_eco	ino_other
artificial intelligence	0.072 (0.014)	0.045 (0.014)	0.023 (0.008)	0.044 (0.011)	0.032 (0.010)	0.012 (0.005)
cloud computing	0.060	0.032 (0.011)	0.054	0.055	0.021	0.015 (0.007)

Independent Variables	Dependent Variables					
	ino_product	ino_process	ino_organizational	ino_marketing	ino_eco	ino_other
	(0.012)		(0.018)	(0.014)	(0.007)	
big data analytics	0.066 (0.013)	0.045 (0.014)	0.055 (0.018)	0.072 (0.017)	0.058 (0.018)	0.016 (0.007)
robotics	0.053 (0.010)	0.112 (0.031)	0.020 (0.007)	−0.006 (0.002)	0.057 (0.018)	0.028 (0.012)
smart devices	0.080 (0.015)	0.064 (0.020)	0.029 (0.010)	0.046 (0.012)	0.138 (0.037)	0.015 (0.007)
blockchain	0.026 (0.005)	0.029 (0.010)	0.054 (0.018)	0.038 (0.010)	0.026 (0.009)	0.024 (0.011)

Marginal effects were taken as average values. Values in parentheses are standard deviations.

Table 5 presents the predicted probability of success. In this context, the observed variable equals 1 for success and 0 for failure (Cappellari & Jenkins, 2003:280). pall0s represents the probability of failure (0) for all advanced digital technology adoptions, whereas pall1s represents the probability of success (1). Across all models, the probability of failure is 39%, whereas the probability of success is 0.3%. In Table 6, based on the sample used in this study, 39.2% of firms do not introduce any innovation, whereas 0.7% implement all types of innovation.

In Table 5, pmarg values present the marginal probability of success for each model. According to the table, the average probability of implementing product innovation, i.e., the probability of success for the first model, is 29%. The probabilities of success for ecological innovation (fifth model, 23%), marketing innovation (fourth model, 22%), process innovation (second model, 21%), organisational innovation (third model, 17%), and other types of innovation (sixth model, 8%) follow product innovation, respectively. The estimated probabilities of success are consistent with the adoption rates of advanced digital technology in the study sample, as presented in Table 6. According to Table 6, product innovation stands out among the innovation types, with a 29% adoption rate. Eco-innovation, marketing, and process innovation follow with 23%, 22%, and 21%, respectively. Organisational innovation follows at 17%, while other types of innovation are at the lowest at 8%.

Table 5

Predicted Probabilities of Success

	Mean	Standard Deviation	Minimum	Maximum
pall0s	0.388	0.184	0.001	0.855
pall1s	0.003	0.011	1.42e-06	0.221
pmarg1 (ino_product)	0.293	0.154	0.042	0.910
pmarg2 (ino_process)	0.210	0.144	0.020	0.927
pmarg3 (ino_organizational)	0.173	0.114	0.014	0.814
pmarg4 (ino_marketing)	0.223	0.119	0.027	0.791
pmarg5 (ino_eco)	0.232	0.148	0.012	0.854
pmarg6 (ino_other)	0.085	0.061	0.009	0.531

Table 6

The proportion of firms implementing innovation in the sample

	Number of firms	Rate of firms
none innovation type	5111	%39.2
all innovation types	86	%0.7
ino_product	3828	%29.3
ino_process	2736	%21
ino_organizational	2249	%17.2
ino_marketing	2886	%22.1
ino_eco	3031	%23.2
ino_other	1109	%8.5

Table 7 summarises the relationship between advanced digital technologies and different types of innovation. The findings indicate a positive relationship between advanced digital technologies and various types of innovation. However, the role of advanced digital technologies in innovation can vary by innovation type. Cloud computing, big data analytics, and smart device technologies are key determinants across all innovation types. Artificial intelligence positively contributes to all innovation types except other innovations, whereas robotics positively influences all types except organisational and marketing innovation. Blockchain technology, on the other hand, exhibits a positive impact on organisational and marketing innovations.

The inherent differences among advanced digital technologies lead to varied impacts across different types of innovation. In the digital transformation process, the prioritisation of advanced digital technologies should align with each country's development goals. Similarly, firms determine the positioning of advanced digital technologies in line with their strategic objectives and growth plans. For instance, blockchain technology may not be a priority for a company focused on product innovation, whereas robotics technology might be less relevant for a firm targeting marketing innovation.

Table 7

Impact of Advanced Digital Technologies on Different Kinds of Innovation

Independent Variables	Dependent Variables					
	ino_product	ino_process	ino_organizational	ino_marketing	ino_eco	ino_other
artificial intelligence	✓	✓	✓	✓	✓	
cloud computing	✓	✓	✓	✓	✓	✓
big data analytics	✓	✓	✓	✓	✓	✓
robotics	✓	✓			✓	✓
smart devices	✓	✓	✓	✓	✓	✓
blockchain			✓	✓		

✓ indicates a positive relationship at a significance level of at least 5%.

Discussion and Conclusion

Studies often focus on independently investigating or predicting one specific type of innovation, which is a crucial part of the literature. Indeed, the correlation coefficients from the multivariate probit estimation suggest that innovation types should be evaluated simultaneously, and that analysing them concurrently is likely to yield more accurate results. A range of factors, including fundamental firm characteristics,

financial status, infrastructure, and the quality of human resources, influence firms' decisions to participate in innovation. Several common factors shape firms' innovation decisions. Consequently, although product, process, or ecological innovation differs from organisational and marketing innovation, innovative firms treat innovation as a cohesive whole across various dimensions, from their products to their marketing strategies. Therefore, regardless of the specific type, different innovation types should be considered simultaneously. However, this approach requires a multivariate probit model rather than a commonly employed independent probit model, as it accounts for the correlation between error terms.

The number of employees, participation in a global value chain, market collaboration environment, and export activities determine firms' engagement in innovation. Through exports and collaboration channels, interaction with other institutions supports firms' access to current market information and contributes to the accumulation of knowledge within the firm. The increased knowledge stock triggers innovation reliant on information as an input and help maintain firms' competitiveness.

From a public perspective, the results indicate that policies supporting and enhancing the market should be implemented, as access to other institutions and a collaborative environment drive innovation. Moreover, collaboration has a statistically significant positive impact on innovation that contribute to market performance and sustainability. Product innovations increase firms' market share and a country's brand creation, while ecological innovations stand out for their environmental sensitivity and resource efficiency. Given the crucial role of product and ecological innovation in sustainable growth, the importance of supporting a collaborative environment through public policies becomes clear.

In addition to the well-known benefits of collaborative environments, such as fostering interdisciplinary research, their role in innovation underscores the importance of improving the market environment for developing countries. Organising events that promote university–industry collaborations, establishing the necessary legal framework, and creating platforms to facilitate such cooperation will help mature the market's collaborative structure. These practices are more cost-effective than alternative subsidy policies and contribute to the economy beyond innovation. Therefore, improving the collaborative environment in the market is essential for developing countries to close their technological gaps.

Adopting advanced digital technologies in firms is closely linked to innovation. Given the relationship between sustainable growth and innovation, supporting firms' adoption of advanced digital technologies and accelerating digital transformation is vital. From an innovation perspective, advanced digital technologies should be considered an important component of firms' innovation strategies.

According to the findings, advanced digital technologies can offer solutions to the problem of stagnation, which has become particularly pronounced in economies recently. While the relationship between these technologies and innovation may vary by the type of innovation, they generally play a positive role in accelerating it. Advanced digital technologies can help address stagnation by driving innovation.

On the other hand, the results highlight the importance of advanced digital technologies in enabling developing countries to close their technological gaps and transition to a more innovative position. In a globalised world, particularly challenging conditions, such as recent global shocks and structural transformations, intensify pressure on countries and reshape markets. Developing countries that aim to gain or maintain their positions in these reshaped markets need to participate in the digital transformation process. Policies that improve the collaborative environment of the market are crucial for facilitating firms' digital transformation.

From the perspective of firms, the transition to advanced digital technologies has become vital for enhancing competitiveness and ensuring long-term sustainability. While follower firms must adopt these technologies to improve their market position, leading firms must continuously monitor developments in

digital technologies to maintain their current positions. Given the diversity of advanced digital technologies and the differentiated impact of various technology types, firms must identify priority technologies that align with their strategic goals in the digitalisation process. Accurate evaluation and proper positioning of alternative advanced digital technologies will amplify the potential positive outcomes of digitalisation.

The primary constraint of this study is the lack of datasets that track the digital transformation process by monitoring firms over a long period. With the increasing emphasis on advanced digital technologies, more detailed and long-term datasets are expected to be developed in the coming years. Research using panel datasets will help clarify the effects of advanced digital technologies and allow the evaluation of potential time lags in those effects.

The findings indicate that innovation activities should be considered holistically and that the impact of advanced digital technologies varies by technology type. While many studies represent the economic effects of digitalisation with a single variable, analyses by technology type are essential for accurately positioning advanced digital technologies and identifying priority areas. Future research using longitudinal data will enable a more precise assessment of the long-term impacts of digital transformation.



Ethical Considerations: The study uses survey data from the Flash Eurobarometer, conducted by the European Commission. Flash Eurobarometer surveys target firms and contain firm-specific data. To maintain confidentiality, these datasets are provided in an anonymized format, ensuring firm-level data protection. Due to confidentiality requirements, the dataset used in this study is not publicly available as open data. However, researchers can access the dataset through the database after agreeing to the specified usage terms, enabling them to conduct their analyses in compliance with data protection regulations.

Peer Review: Externally peer-reviewed.

Author Contributions: Conception/Design of Study- Ö.F., H.Ş.; Data Acquisition- Ö.F.; Data Analysis and Interpretation- Ö.F.; Drafting Manuscript- Ö.F.; Critical Revision of Manuscript- Ö.F., H.Ş.; Final Approval and Accountability- Ö.F., H.Ş.; Supervision- H.Ş.

Conflict of Interest: The authors have no conflict of interest to declare.

Grant Support: The author declared that this study has received no financial support.

Author Details

Özlem Fikirli (Dr. Öğr. Üyesi)

[1] Bartın University, Faculty of Economics and Administrative Sciences, Department of Economics, Bartın, Türkiye

0000-0002-4003-7276 ozlem_fikirli@hotmail.com

Hasan Şahin (Prof. Dr.)

[2] Ankara University, Faculty of Political Science, Department of Economics, Ankara, Türkiye

0000-0001-5922-068X

References

Adams D., & Hess M. (2010). Social innovation and why it has policy significance. *The Economic and Labour Relations Review*, *21*(2), 139-155. https://doi.org/10.1177/103530461002100209

Antonelli, C. (2017). Digital knowledge generation and the appropriability trade-off. *Telecommunications Policy, 41*(10), 991-1002. https://doi.org/10.1016/j.telpol.2016.12.002

Arvanitis, S., Kyriakou, N., & Loukis, E. N. (2017). Why Do Firms Adopt Cloud Computing? A Comparative Analysis Based on South and North Europe Firm Data. *Telematics and Informatics, 34*(7), 1322-1332. doi: 10.1016/j.tele.2016.05.013

Ballestar, M. T., Díaz-Chao, Á., Sainz, J., & Torrent-Sellens, J. (2020). Knowledge, robots, and productivity in SMEs: Explaining the second digital wave. *Journal of Business Research, 108*, 119-131. https://doi.org/10.1016/j.jbusres.2019.11.017

Büyüközkan, G., & Göçer, F. (2018). Digital Supply Chain: Literature review and a proposed framework for future research. *Computers in Industry, 97*, 157-177. https://doi.org/10.1016/j.compind.2018.02.010

Cappellari, L., & Jenkins, S. P. (2003). Multivariate probit regression using simulated maximum likelihood. *STATA Journal, 3*(3), 278-294. https://doi.org/10.1177/1536867X0300300305

Ciarli, T., Kenney, M., Massini, S., & Piscitello, L. (2021). Digital technologies, innovation, and skills: Emerging trajectories and challenges. *Research Policy, 50*(7), 104289. doi: 10.1016/j.respol.2021.104289

DeStefano, T., Kneller, R., & Timmis, J. (2020). *Cloud computing and firm growth*. CESifo Working Papers, No. 8306. https://dx.doi.org/10.2139/ssrn.3618829

DiMaggio, P. (1998). The New İnstitutionalisms: Avenues of Collaboration. *Journal of Institutional and Theoretical Economics*/Zeitschrift für die gesamte Staatswissenschaft, *154*(4), 696-705. https://www.jstor.org/stable/40752104

European Commission, Brussels (2020). *Flash Eurobarometer 486 (SMEs, start-ups, scale-ups*, and entrepreneurship*)*. GESIS Data Archive, Cologne. ZA7637 Data file Version 2.0.0, https://doi.org/10.4232/1.13639.

Ferraris, A., Mazzoleni, A., Devalle, A., & Couturier, J. (2019). Big Data Analytics Capabilities and Knowledge Management: Impact on Firm Performance. *Management Decision, 57*(8), 1923-1936. https://doi.org/10.1108/MD-07-2018-0825

Ferreira, J. J., Fernandes, C. I., & Ferreira, F. A. (2019). To Be or Not to Be Digital, That Is The Question: Firm Innovation and Performance. *Journal of Business Research, 101*, 583-590. doi: 10.1016/j.jbusres.2018.11.013

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

Greene, W. H. (2003). *Econometric analysis* (Fifth Edition). Pearson Education, New Jersey.

Heyman, F., Norbäck, P. J., & Persson, L. (2021). *Artificial intelligence, robotics, work, and productivity: The role of firm heterogeneity*. IFN Working Paper, No: 1382. http://hdl.handle.net/10419/240525

Hobday, M. (2005). Firm-level innovation models: perspectives on research in developed and developing countries. *Technology analysis & strategic management, 17*(2), 121-146. https://doi.org/10.1080/09537320500088666

Hsu, P. F., Kraemer, K. L., & Dunkle, D. (2006). Determinants of e-business use in US firms. *International Journal of Electronic Commerce, 10*(4), 9-45. https://doi.org/10.2753/JEC1086-4415100401

Kastelli, I., Dimas, P., Stamopoulos, D., & Tsakanikas, A. (2024). Linking digital capacity to innovation performance: The mediating role of absorptive capacity. *Journal of the Knowledge Economy, 15*(1), 238-272. https://doi.org/10.1007/s13132-022-01092-w

Kimani, D., Adams, K., Attah-Boakye, R., Ullah, S., Frecknall-Hughes, J., & Kim, J. (2020). Blockchain, business and the fourth industrial revolution: Whence, whither, wherefore and how? *Technological Forecasting and Social Change, 161*, 120254. https://doi.org/10.1016/j.techfore.2020.120254.

Kong, T., Sun, R., Sun, G., & Song, Y. (2022). Effects of digital finance on green innovation considering information asymmetry: An empirical study based on Chinese listed firms. *Emerging Markets Finance and Trade, 58*(15), 4399-4411. https://doi.org/10.1080/1540496X.2022.2083953

Kshetri, N. (2011). Cloud Computing in the Global South: drivers, effects, and policy measures. *Third World Quarterly, 32*(6), 997-1014. doi: 10.1080/01436597.2011.586225

Léger, A., & Swaminathan, S. (2007). *Innovation theories: Relevance and implications for developing country innovation*. DIW Discussion Papers, No. 743. http://hdl.handle.net/10419/27267

Maresova, P., Soukal, I., Svobodova, L., Hedvicakova, M., Javanmardi, E., Selamat, A., Krejcar, O. (2018). Consequences of Industry 4.0 in Business and Economics. *Economies*, *6*(3), 46. https://doi.org/10.3390/economies6030046

Müller O., Fay M., & Vom Brocke J. (2018). The Effect of Big Data and Analytics on Firm Performance: An Econometric Analysis Considering Industry Characteristics. *Journal of Management Information Systems, 35*(2), 488-509. doi: 10.1080/07421222.2018.1451955

Nambisan, S., Wright, M., & Feldman, M. (2019). The digital transformation of innovation and entrepreneurship: progress, challenges, and key themes. *Research Policy, 48*(8), 103773. doi: 10.1016/j.respol.2019.03.018

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. doi: 10.1080/10438599.2018.1493075

North, D. C. (1990). *Institutions, institutional change, and economic performance*. Cambridge University Press.

OECD (2005). Oslo manual guidelines for collecting and interpreting innovation data. Paris: OECD/Euro-stat. Third edition.

OECD (2019). *Measuring the Digital Transformation: A Roadmap for the Future*. OECD Publishing, Paris. https://doi.org/10.1787/5acf6594-en.

Rammer, C., Czarnitzki, D., & Fernández, G. P. (2021). *Artificial Intelligence and Industrial Innovation: Evidence from Firm-Level Data*. ZEW-Centre for European Economic Research Discussion Paper, (21-036). https://dx.doi.org/10.2139/ssrn.3829822.

Remes, J., Mischke, J., Krishnan, M. (2018). Solving the Productivity Puzzle: The Role of Demand and the Promise of Digitization. *International Productivity Monitor, 35*, 28-51.

Rennings, K. (2000). Redefining innovation—eco-innovation research and the contribution from ecological economics. *Ecological Economics*, *32*(2), 319-332. doi: 10.1016/S0921-8009(99)00112-3

Sagar, S. (2024). The impact of digital transformation on retail management and consumer behavior. *Journal of Business and Management*, *26*(1), 06-14. doi: 10.9790/487X-2601010614

Sternberg, R., & Arndt, O. (2001). The firm or the region: What determines the innovation behavior of European firms? *Economic geography, 77*(4), 364-382. https://doi.org/10.1111/j.1944-8287.2001.tb00170.x

Tirole, J. (2023). Competition and the industrial challenge for the digital age. *Annual Review of Economics*, *15*(1), 573-605. https://doi.org/10.1146/annurev-economics-090622-024222

Van Ark, B. (2015). Productivity and digitilization in Europe: Paving the road to faster growth. *Digiworld Economic Journal, 100*, 107-124. https://ssrn.com/abstract=2845368

World Economic Forum (2017). *Harnessing Fourth Industrial Revolution technologies for sustainable development*. World Economic Forum. https://www3.weforum.org/docs/WEF_Harnessing_the_4IR_for_the_Earth.pdf

Zhang, X. E., Wang, W., Teng, X., & Yang, L. (2024). Navigating Competitive Intensity: The Role of Digital Orientation in SMEs' Green Innovations. *Journal of the Knowledge Economy*, 1-29. https://doi.org/10.1007/s13132-024-02110-9

Zhao, J., Hu, P., & Cui, L. (2025). Economic and non-economic impact of digital transformation on enterprise competitiveness: Evidence from Chinese-listed companies. *Technology Analysis & Strategic Management*, 37(13), 4645-4661. https://doi.org/10.1080/09537325.2025.246792.