World Journal of Applied Economics (2024), 10(2): 43-54
doi: 10.22440/wjae.10.2.1 econworld
Research Article

Drivers of Advanced Digital Technologies[a]

Özlem Fikirli[b] Hasan Şahin[c]

Received: 08.05.2024; Revised: 10.06.2024; Accepted: 27.06.2024

Advancements in digital technologies, especially computer and information systems, force firms to adopt them in their production processes. Artificial intelligence, cloud computing, big data analytics, robotics, smart devices, and blockchain are the leading advanced technologies. This study explores the drivers of firms' adoption of these technologies by estimating a multivariate probit model utilizing a Eurobarometer dataset. A statistically significant and positive correlation between the error terms of all models indicates that investigating the adoption of all advanced digital technologies together is more appropriate than independent analyses. Drivers of advanced digital technologies appear similar with decisive factors in using new technologies, and implementation of any type of innovation significantly increases the probability of adoption. The other determinants are the firm size, interaction with international markets, and the network structure of the market in which firms operate. Furthermore, location positively impacts the adoption of cloud computing and big data analytics, while it exerts no significant influence on the adoption of other types of advanced digital technologies.

JEL codes: D22, D83, 033

Keywords: Digital technology, Technology diffusion, Multivariate probit model

1 Introduction

In line with the nature of technology, advancements in digital technologies have accelerated exponentially. The digitalization process in the 20^{th} century, which emerged via the internet and websites, has evolved into more complex structures with enhancements in computer technologies and information systems. Traditional data concepts transformed into big data, which led to the introduction of big data analytics. Accessing and processing big data from different production locations requires cloud computing technologies. Artificial intelligence technology, promising advancements in data selection, evaluation, decision-making, and more, has become increasingly prevalent. Additionally, interest in robotics and smart devices, which are automation technologies enhanced with other technologies, is rising. These new technologies and their advancements are expected to continue based on the nature of technology, and the evolution of digital technologies will reshape economies.

[a] An earlier version of the study was presented at the ICE-TEA 2023 conference in Antalya on November 16-18, 2023. We thank the editor, two anonymous referees, and conference participants for their valuable comments and suggestions.

[b] Corresponding author. Department of Economics, Faculty of Economics and Administrative Sciences, Bartın University, Bartın, Turkey. email: ozlem_fikirli@hotmail.com 0000-0002-4003-7276

[c] Department of Economics, Faculty of Political Science, Ankara University, Ankara, Turkey. email: hasansahin68@gmail.com 0000-0001-5922-068X

Catch-up of technology becomes more prominent in the digitalization process as progress in digital technologies continues since technological gaps and the costs of catch-up of this process increase cumulatively. Furthermore, the added value and positive impact of the transition to digital technologies decrease over time. Therefore, it is of great importance to define digital transformation road-maps and swiftly implement action plans.

The attitude of countries toward digital technologies can indeed vary despite many opportunities, such as increased productivity and decreased costs. Different views on the digitalization process are evident at the micro-level, particularly across firms. Additionally, there is significant diversity among European Union (EU) countries that adhere to the Digital Single Market Strategy. For example, the adoption rate of cloud computing stands at 45.4% in the EU, whereas it is 13.6% in Bulgaria and 71.1% in Ireland. Regarding big data analytics, the adoption rates among firms are 10.3% in EU countries, 3.5% in Romania, and 23.5% in the Netherlands (Eurostat, 2024).

Understanding the factors determining firms' transition to advanced digital technologies is crucial for countries to develop accurate and effective action plans for digital transformation. Identifying these factors will lay the groundwork for pinpointing firms that need support or may risk losing competitiveness in the face of digitalization. Additionally, comparing the determinants of transitioning to advanced digital technologies with those of adoption of other technologies is essential for providing insights into the nature of advanced digital technologies. The main motivation of this study is to investigate the underlying foundations of variations in firms' attitudes toward advanced digital technologies. It also examines the similarities between the drivers of advanced digital technologies and other new technologies.

The main contribution of this study is its comprehensive evaluation of advanced digital technologies, exploring the adoption of various types of these technologies. To the best of our knowledge, no study concurrently analyzed the adoption of multiple types of advanced digital technologies. Furthermore, this study examines the relationship between the adoption decisions for different types of advanced digital technologies using a multivariate probit model to estimate the correlations among them. Additionally, this study utilizes a survey conducted on an extensive sample.

The plan of the paper is as follows. Section 2 provides a literature review on technology adoption and the essential structure of the adoption process. Section 3 explains the data and method, and Section 4 presents the estimation findings. Finally, Section 5 consists of the latest considerations, suggestions, and limitations of the study.

2 Literature

Adopting technology is transitioning to or using new technology for organizations, e.g., firms, through reconfiguring the production process, organizational structure, supply chain, etc., where technology integration is affected. Hence, adopting technology results in modifications or improvements within firms regarding their technological preferences.

The advantages of the digitalization process have expanded and deepened with the advanced digital technologies. Increasing productivity (Ballestar et al., 2020), competitiveness, speed (De Caria, 2017), quality of production (DeStefano & Timmis, 2024), product diversity, international trade (Denicolai et al., 2021), employment (Kromann et al., 2020), revenue (Xu et al., 2021), performance (Ferraris et al., 2019), and innovation (Rammer et al., 2021), coupled with the minimization of costs (Nicholas-Donald et al., 2018), time, waste

(Pellegrini et al., 2021) information asymmetries, etc., constitute the core of these advantages. The importance of transitioning to advanced digital technologies becomes evident upon considering these benefits.

Technology adoption is significantly shaped by knowledge accumulation. Innovation, which is widely used as one of the primary indicators for the knowledge-based structure, also becomes prominent in adopting advanced digital technologies (Kshetri, 2011; Alshamaila et al., 2013; Giotopoulos et al., 2017). Knowledge accumulation facilitates both the evaluation of alternative technologies and their efficient integration. Firms implementing innovation generally hold positive attitudes towards new technology and are well-informed about its advantages. Therefore, it is expected that these firms view the adoption of new technology favorably and have a higher probability of adoption compared to non-innovative firms (Arvanitis et al., 2017; Giotopoulos et al., 2017; Loukis et al., 2017; Zolas et al., 2021).

Access to international markets increases knowledge accumulation and indirectly enhances the knowledge-based structure. The knowledge capacities of firms operating in global markets increase through interactions with different actors, such as firms, organizations, and consumers, facilitating the transfer of new knowledge between the firms. This increase in knowledge capacities triggers knowledge creation that has an exponential nature. The probability of firms engaging in international markets increases due to these knowledge-based impacts, and the domino effect appears in this way. As a result, firms participating in global markets are more inclined to adopt new technologies (Masayuki, 2016).

The literature states that firm characteristics are the main determinants of adopting new (Tornatzky & Fleischer, 1990; Rogers, 1995; Molinillo & Japutra, 2017) and digital technologies (Chatzoglou & Chatzoudes, 2016; Kossaï et al., 2020). Firm characteristics emerge as significant factors when adopting advanced digital technologies, such as cloud computing and artificial intelligence, alongside fundamental digital technologies like the internet, e-commerce, and web pages (Ohnemus & Niebel, 2016; Zolas et al., 2021).

Advanced digital technologies require essential digital infrastructures such as the Internet. Due to the expensive investment costs, the current infrastructure cannot support digital transformation everywhere. Operating in big cities, which typically boast more complex infrastructures and are ahead in digitalization, appears to significantly influence the adoption of digital technologies (Giotopoulos et al., 2017). In other words, the firm's location is crucial in the transition to advanced digital technologies.

Collaboration, an emphasized phenomenon in new institutional economics, leads to a transformation in decision mechanisms. According to this perspective, economic actors optimize their utility under constraints, but their utility functions are updated and altered, and they can achieve maximum utility through collaboration despite the competitive markets. The interaction of economic actors via collaboration results in the transfer of tacit knowledge and a reduction in knowledge costs. The collaboration structure or network pattern of the market, shaped by this phenomenon, can accelerate the integration of new technologies due to its knowledge-based effects. Moreover, this market environment is expected to be a key factor in transitioning to advanced digital technologies (Giotopoulos et al., 2017).

Despite the critical importance of digital transformation, studies investigating the adoption of advanced digital technologies remain scarce, mainly due to the lack of available data. Recent surveys have been designed through the growing interest in advanced digital technologies and the emergence of new types of these technologies. Moreover, new projects and research efforts have been initiated to evaluate the economic impact of these advancements.

Although the need for data has prompted efforts to gather it, data generation is a time-consuming process. In literature, most studies examining the adoption of advanced digital technologies focus on a single type of technology (Ohnemus & Niebel, 2016; Arvanitis et al., 2017; Loukis et al., 2017; Nicoletti et al., 2020). However, only a few studies analyze multiple types of advanced digital technologies. For example, (Zolas et al., 2021) investigated the adoption of artificial intelligence, cloud computing, and robotics technology in U.S. firms.

3 Data and Method

Diffusion theories of new technology can be evaluated in three main categories: contagion, social influence, and social learning. In economics, the social learning model is the most suitable as it considers the role of knowledge diffusion in firm decision-making (Young, 2009). This study examines the drivers of advanced digital technologies through the social learning model, where the network structure of the market represents knowledge diffusion between firms. Additionally, firms' export activities, which serve as a channel for knowledge transfer; innovation activities, as a proxy for a firm's knowledge-based structure; and firm characteristics highlighted in the literature, are also included in the model. All these variables are assumed to play a decisive role in adopting advanced digital technologies (Masayuki, 2016; Arvanitis et al., 2017; Giotopoulos et al., 2017; Zolas et al., 2021).

This study investigates drivers of adoption of advanced digital technologies using a multivariate probit model as shown in equations (1) and (2) (Cappellari & Jenkins, 2003).

$$y^*_{ik} = \beta'_k \; x_{ik} \; + \epsilon_{ik} \tag{1}$$

$$y_{ik} = \begin{cases} 1, y^*_{ik} > 0 \\ 0, y^*_{ik} \leq 0 \end{cases} \tag{2}$$

where $y^*_{ik}, \beta'_k, x_{ik}, \epsilon_{ik}$, and y_{ik} are the continuous unobservable variables, coefficients, independent variables, the error term that has zero mean, and the observed counterpart of y^*_{ik}, respectively, i stands for the firm, and k is the set of advanced technologies that are considered dependent variables: artificial intelligence, cloud computing, big data, robotics, smart devices, and blockchain. The variance-covariance matrix of error terms has diagonal elements equal to 1 and symmetrically equal off-diagonal elements. Definitions and descriptive statistics of variables are provided in Table 1 and Table 2, respectively.

The "SMEs, Start-ups, Scale-ups, and Entrepreneurship Survey" conducted in 2020 provides detailed information about the transition to advanced digital technologies and is used in this study.[1] To our knowledge, no other open-access survey offers as elaborate and comprehensive data as this one. The survey covers micro-enterprises (60% of the sample), small enterprises (20%), medium-sized enterprises (15%), and large enterprises (5%) across 39 countries, including the 27 Member States of the EU, Bosnia and Herzegovina, Brazil, Canada, Iceland, Japan, Kosovo, North Macedonia, Norway, Serbia, Türkiye, the UK, and the USA. So, the data has a cross-sectional nature. As a result, variables related to time and shifts in firm attitudes toward advanced digital technologies cannot be examined due to the absence of longitudinal data.

[1] It is one of the European Commission's Flash Eurobarometer survey, which are ad-hoc thematic surveys on a specific topic. For more information, see `https://europa.eu/eurobarometer/about/eurobarometer`.

Table 1: Description of variables

Variables	Description
Dependent Variables	
artificial intelligence	1 if the firm adopted artificial intelligence, else=0
cloud computing	1 if the firm adopted cloud computing, else=0
big data	1 i the firm adopted big data analytics, else=0
robotics	1 if the firm adopted robotics, else=0
smart devices	1 if the firm adopted smart devices, else=0
blockchain	1 if the firm adopted blockchain, else=0
Independent Variables	
innovation	1 if the firm has implemented any innovation in the last 12 months, else=0
size	Natural log of employees
location	1 if the firm is in a large town or city, else=0
exports	1 if the firm exported goods or services in 2019, else=0
network	Access to and network with business partners (other enterprises, public sector, educational institutions, research organizations, etc.) Very good=4, Fairly good=3, Fairly poor=2, Very poor=1

Note: Country and sector dummies are also controlled for.

More than one binary dependent variable requires the estimation of multivariate probit or logit models. With the easy implementation of correlation structures, and the availability of ready-made software and the common use in empirical studies (Cameron & Trivedi, 2005; Wooldridge, 2007), we have several theoretical and practical motivations for using a multivariate probit rather than a multivariate logit model.

Table 2: Descriptive statistics of variables

Variables	Mean	Std. Dev.	Min.	Max.
artificial intelligence	0.080	0.271	0.000	1.000
cloud computing	0.489	0.500	0.000	1.000
big data	0.152	0.359	0.000	1.000
robotics	0.090	0.286	0.000	1.000
smart devices	0.287	0.452	0.000	1.000
blockchain	0.035	0.183	0.000	1.000
size	2.394	1.637	0.000	9.200
location	0.495	0.500	0.000	1.000
innovation	0.629	0.483	0.000	1.000

The multivariate probit model considers the correlation between the error terms of estimated equations, and the Wald test, the likelihood ratio test and the Lagrange multiplier statistic are commonly used to test the presence of such correlation (Greene, 2003). If the null hypothesis of no correlation between the error terms is not rejected, the equations should be estimated separately. In the multivariate probit models, the observed variable takes two values: one for success, zero for failure (Cappellari & Jenkins, 2003).

4 Results and Discussion

The estimated coefficients of the multivariate probit model are summarized in Table 3. The presence of correlations between the error terms of the equations is investigated using the Likelihood Ratio test. The null hypothesis, which states no correlation between the error terms, is not rejected according to the test results. The chi-square test confirms that estimating the equations simultaneously rather than separately is more appropriate.

In other words, examining advanced digital technologies simultaneously can produce more accurate results that play an essential role in prescribing applied policies. There is a positive and statistically significant relationship between all error terms at the 1% significance level. The dependent variables of Models 1 through 6 are the adoption of artificial intelligence, cloud computing, big data analytics, robotics, smart devices, and blockchain, respectively. For instance, rho 21 indicates the correlation between the error terms of Model 2 (cloud computing) and Model 1 (artificial intelligence).

Table 3: Results of multivariate probit estimation (coefficients)

	Dependent Variables					
Independent Variables	artificial intelligence (1)	cloud computing (2)	big data (3)	robotics (4)	smart devices (5)	blockchain (6)
size	0.116*** (0.011)	0.104*** (0.008)	0.179*** (0.009)	0.182*** (0.011)	0.137*** (0.009)	0.090*** (0.013)
location	0.074* (0.041)	0.165*** (0.026)	0.167*** (0.029)	0.044 (0.041)	0.006 (0.033)	0.091* (0.047)
innovation	0.411*** (0.045)	0.362*** (0.026)	0.437*** (0.039)	0.443*** (0.043)	0.453*** (0.032)	0.368*** (0.050)
exports	0.316*** (0.044)	0.247*** (0.025)	0.241*** (0.034)	0.341*** (0.045)	0.161*** (0.024)	0.114** (0.051)
network	0.051*** (0.017)	0.056*** (0.016)	0.066*** (0.024)	0.063** (0.027)	0.035** (0.015)	0.073** (0.034)
constant	-2.474*** (0.148)	-0.111 (0.155)	-2.101*** (0.210)	-2.376*** (0.200)	-0.838*** (0.119)	-2.687*** (0.242)
	Correlation Coefficient			**Standard Errors**		
rho 21	0.157***			(0.018)		
rho 31	0.319***			(0.024)		
rho 41	0.315***			(0.021)		
rho 51	0.266***			(0.019)		
rho 61	0.303***			(0.032)		
rho 32	0.309***			(0.020)		
rho 42	0.140***			(0.026)		
rho 52	0.256***			(0.015)		
rho 62	0.328***			(0.027)		
rho 43	0.184***			(0.023)		
rho 53	0.270***			(0.018)		
rho 63	0.369***			(0.023)		
rho 54	0.258***			(0.018)		
rho 64	0.239***			(0.033)		
rho 65	0.258***			(0.016)		
Likelihood ratio test H0: all rho values are 0				Chi-Square (15) = 2084.4 Prob = 0.000		
Number of Observations				14,108		

Note: The values in parentheses represent country-clustered robust standard errors. *, **, and *** indicate the significance levels of 10%, 5%, and 1%, respectively. Country characteristics are considered.

According to Table 3, drivers of advanced digital technologies seem similar to decisive factors of adopting new technologies, and these results of the multivariate probit model are consistent with the literature (Masayuki, 2016; Giotopoulos et al., 2017; Zolas et al., 2021). There is a significant positive relationship between firm size and the adoption of advanced digital technologies at the 1% significance level. Larger firms benefit from various advantages, including access to financial resources and qualified human capital that also facilitate the adoption of advanced digital technologies.

The firm's location is a positive and strong (weak) determinant of adopting artificial intelligence and blockchain (cloud computing and big data analytics). However, no effect of location on the adoption of robotics and smart devices indicates that operating in an urban area is not a prerequisite for adopting automation technologies.

The knowledge-based structure of a firm is another crucial factor influencing the adoption of advanced digital technologies. There exists a statistically significant and positive relationship between innovation and the adoption of advanced digital technologies. Firms that implement innovation are more inclined to advanced digital technologies. Positive externalities, particularly an increase in knowledge accumulation stemming from innovation, are key factors in this tendency towards advanced digital technologies.

Consequently, knowledge accumulation is triggered through export channels. Furthermore, exporter firms typically possess substructure and development levels that are more conducive to the transition to new technologies.

The network pattern of the market stands out as another crucial determinant influencing the diffusion of advanced digital technologies. The relationship between the network structure of the market and the adoption of advanced digital technologies exhibits a positive orientation and is statistically significant, at least at the 5% level. Improvements in network patterns prompt a shift towards advanced digital technologies. Thus, in contrast to a competitive approach, collaboration serves to facilitate the digital transformation of firms and consequently contributes to firm performance in this way.

According to the marginal effects of the probit model provided in Table 4, a 1% increase in the number of employees leads to a rise in the probability of adopting an advanced technology between 0.5% (blockchain) and 3.7% (smart devices). Being in a large town or city is associated with increased adoption probabilities of 5.7% and 3.4% for cloud computing and big data analytics technologies, respectively. Innovation results in the rise of adoption probabilities of advanced technologies ranging from 2.3% (blockchain) to 13.7% (smart devices). Being an exporting firm increases the probability of adoption of cloud computing the most (by 8.5%), whereas it affects the probability of adoption of blockchain the lowest (by 0.8%). Improvement in the network structure of the market also contributes to increases in the adoption probabilities, and its impact is the highest (lowest) for cloud computing (blockchain) at 1.9% (0.5%).

Table 4: Marginal effects

	Dependent Variables					
Independent Variables	artificial intelligence (1)	cloud computing (2)	big data (3)	robotics (4)	smart devices (5)	blockchain (6)
size	0.012 (0.013)	0.033 (0.026)	0.030 (0.026)	0.018 (0.017)	0.037 (0.028)	0.005 (0.005)
location	0.009 (0.007)	0.057 (0.010)	0.034 (0.018)	0.006 (0.005)	-0.002 (0.000)	0.006 (0.005)
innovation	0.048 (0.032)	0.126 (0.021)	0.083 (0.041)	0.054 (0.041)	0.137 (0.031)	0.023 (0.016)
exports	0.043 (0.028)	0.085 (0.015)	0.050 (0.025)	0.048 (0.033)	0.050 (0.012)	0.008 (0.006)
network	0.007 (0.005)	0.019 (0.004)	0.014 (0.007)	0.009 (0.007)	0.011 (0.003)	0.005 (0.004)

Note: Marginal effects are taken at the mean values. The values in parentheses represent standard errors.

The marginal effects calculated in the predicted model serve as compelling evidence of the significance of a knowledge-based structure. Specifically, the estimated values underscore the crucial role of knowledge-based firms in driving digital transformation. The emphasis on supporting innovation emerges as a prominent factor contributing to digital transformation, highlighting the substantial impact of innovation implementation. Moreover, rather than competitive markets, collaborative patterns within markets hold promise for catalyzing the digital transformation process.

The figures in Table 5 show the success probability of the observed variable, and Table 6 provides the number and fraction of advanced digital technology adopted firms in the sample. The probability of the observed variable, $pall0s$, being zero for all advanced digital technologies is 36.3%, while the probability of adopting all advanced digital technologies, $pall1s$, is 0.2%, as shown in Table 5. Table 6 indicates that 37.1% of firms have not adopted any advanced digital technologies, and 0.33% of firms have adopted all advanced digital technologies. Thus, the predicted probabilities and observed adoption rates are consistent, indicating that the estimated model performs well in terms of prediction capability. The high (low) not-adopting (adopting) probabilities align with expectations, as the diffusion of new technologies requires time for many reasons. Firms need time to acquire information about new technologies and their potential applications, develop their infrastructure or organizational structures to integrate them, learn how to adapt the technologies to their specific needs, and strategically allocate their financial resources over time.

Table 5: Probability of success

Variables	Mean	Std. Dev.	Min.	Max.
pall0s	0.363	0.205	0.002	0.935
pall1s	0.002	0.006	0.000	0.128
pmarg1	0.080	0.082	0.000	0.680
pmarg2	0.489	0.205	0.028	0.989
pmarg3	0.152	0.128	0.001	0.811
pmarg4	0.090	0.103	0.000	0.712
pmarg5	0.287	0.149	0.019	0.848
pmarg6	0.035	0.033	0.000	0.295

The values of $pmarg1 - pmarg6$ demonstrate the success of adopting advanced digital technology, where the number refers to the technology as in the order provided in Table 4, e.g., the value of $pmarg1$ represents the success probability of artificial intelligence. In addition to the values of $pall0s$ and $pall1s$, the very close values of the probabilities derived from the probit model (Table 5) and the sample characteristics (Table 6) for each advanced digital technology indicates that the model's prediction performance is wey well.

Table 6: Adoption of advanced digital technology in the sample

Technology	Number of Firms	Fraction of Firms (%)
none	5,237	37.12
all digital technologies	47	0.33
artificial intelligence	1,131	8.02
cloud computing	6,898	48.89
big data	2,145	15.20
robotics	1,266	8.97
smart devices	4,051	28.71
blockchain	492	3.49

Cloud computing emerges as the leading advanced digital technology, boasting a substantial adoption rate of 49%, as depicted in Table 6. It is followed by smart device technology, with a 29% adoption rate. Subsequently, firms exhibit a preference for big data analytics (15%), robotics (9%), artificial intelligence (8%), and blockchain (3%) technologies, respectively. Blockchain technology ranks last among advanced digital technologies primarily due to its relative novelty and the limited information available regarding its application areas.

5 Conclusion

Advanced digital technologies, stemming from advancements in computer technologies and information systems, lead to the evolution of the digitalization process. In this process, the significance of technology gaps and catch-up models becomes increasingly pronounced. The immediate integration of digital technologies is crucial for harnessing their opportunities. Despite this importance, some firms choose not to adopt advanced digital technologies, while others do. Why does this discrepancy exist? Understanding the answer to this question can serve as a guiding principle for policymakers and aid in determining the necessary policies to foster digital transformation.

Our multivariate probit analyses indicate that conducting a comprehensive examination of all advanced digital technologies together can yield more accurate and insightful results than independent analyses of each technology. This integrated approach allows for a deeper understanding of the interconnectedness between different technologies and integration within firms and markets.

In the analyses, cloud computing stands out as the most prominent and widely recognized technology across advanced digital technologies. Conversely, artificial intelligence and blockchain technologies are often perceived as less desirable, primarily due to their relatively new and complex nature. To address this, it becomes imperative to highlight the application areas and potential integration of these technologies into different fields. Artificial intelligence and blockchain should lead digital transformation roadmaps, focusing on elucidating their practical applications and benefits. Moreover, robotics emerges as another technology with lower adoption rates, likely due to the significant investment costs associated with implementation. To incentivize the adoption of robotics, subsidies and financial support mechanisms can be essential in facilitating the transition towards robotic technologies.

Determining the main factors of the transition to advanced digital technologies is necessary to understand the nature of advanced digital technologies and facilitate their widespread adoption. The drivers of advanced digital technologies share similarities with the determinants of other new technologies, indicating that the adoption of advanced digital technologies can be assessed within the framework of diffusion theories. By applying these theories, researchers and policymakers can gain a deeper understanding of the factors that drive or inhibit adoption, thereby informing strategies to accelerate the diffusion process and maximize the benefits of these technologies for individuals, organizations, and society.

The main drivers of advanced digital technologies are firm characteristics, such as being an innovative, i.e., knowledge-based firm and having access to global markets. On the other hand, location is a critical factor in both cloud computing and big data analytics.

Comparatively small, non-exporting, and non-innovative firms, generally defined by their weak competitive advantage, are followers of advanced digital technologies. Moreover, opportunities that emerge from these technologies deepen the disparity among firms. Consequently, these technologies exacerbate technological gaps and competitive advantages across firms. Thus, firms with these characteristics should be prioritized in subsidy policies to achieve the EU Digital Single Market target. Additionally, the issue of deep technological gaps that result from lag in digital technologies must be considered for countries that are followers and have constrained financial resources. To bridge these technological gaps and seize the opportunities presented by advanced digital technologies, follower countries can learn from existing findings and take proactive steps to accelerate their digital transformation.

Besides the firm characteristics, the network structure of the market in which the firm operates is another driver of adopting advanced digital technologies. Advancements in market collaboration structures and ecosystems can catalyze digital transformation, contrasting with the competitive approach. Namely, the market structure has evolved into a more conducive outlook for knowledge-based economies through digital transformation. Subsidizing the new ecosystem, particularly collaboration patterns with appropriate policies, can facilitate access to the opportunities provided by advanced digital technologies.

The availability of data limits this study. The survey does not list application areas or implementation procedures of advanced digital technologies. This information can shape the determinants of adopting advanced digital technologies. Future research endeavors that access more comprehensive datasets could benefit from considering the application properties of advanced digital technologies. By addressing these limitations and conducting more nuanced analyses considering the diverse application contexts of advanced digital technologies, researchers can provide valuable insights into the drivers of adoption, ultimately informing more effective strategies for promoting digital transformation.

References

Alshamaila, Y., Papagiannidis, S., & Li, F. (2013). Cloud computing adoption by SMEs in the north east of England: A multi-perspective framework. *Journal of Enterprise Information Management*, *26*(3), 250-275. doi:10.1108/17410391311325225

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

Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics: Methods and Applications.* Cambridge University Press.

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

Chatzoglou, P., & Chatzoudes, D. (2016). Factors affecting e-business adoption in SMEs: An empirical research. *Journal of Enterprise Information Management*, *29*(3), 327-358. doi:10.1108/JEIM-03-2014-0033

De Caria, R. (2017). A digital revolution in international trade? The international legal framework for blockchain technologies, virtual currencies and smart contracts: challenges and opportunities. In *Modernizing International Trade Law to Support Innovation and Sustainable Development. Proceedings of the Congress of the United Nations Commission on International Trade Law. Vienna, 4-6 July 2017* (p. 105-117).

Denicolai, S., Zucchella, A., & Magnani, G. (2021). Internationalization, digitalization, and sustainability: Are SMEs ready? A survey on synergies and substituting effects among growth paths. *Technological Forecasting and Social Change*, *166*, 120650. doi:10.1016/j.techfore.2021.120650

DeStefano, T., & Timmis, J. (2024). Robots and export quality. *Journal of Development Economics*, *168*, 103248. doi:10.1016/j.jdeveco.2023.103248

Eurostat. (2024). https://ec.europa.eu/eurostat/data/database.

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. doi:10.1108/MD-07-2018-0825

Giotopoulos, I., Kontolaimou, A., Korra, E., & Tsakanikas, A. (2017). What drives ICT adoption by SMEs? Evidence from a large-scale survey in Greece. *Journal of Business Research*, *81*, 60-69. doi:10.1016/j.jbusres.2017.08.007

Greene, W. H. (2003). *Econometric analysis* (5th ed.). Pearson Education, New Jersey.

Kossaï, M., de Souza, M. L. L., Zaied, Y. B., & Nguyen, P. (2020). Determinants of the adoption of information and communication technologies (ICTs): The case of Tunisian electrical and electronics sector. *Journal of the Knowledge Economy*, *11*(3), 845-864. doi:10.1007/s13132-018-0573-6

Kromann, L., Malchow-Møller, N., Skaksen, J. R., & Sørensen, A. (2020). Automation and productivity—a cross-country, cross-industry comparison. *Industrial and Corporate Change*, *29*(2), 265-287. doi:10.1093/icc/dtz039

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

Loukis, E., Arvanitis, S., & Kyriakou, N. (2017). An empirical investigation of the effects of firm characteristics on the propensity to adopt cloud computing. *Information Systems and e-Business Management*, *15*, 963-988. doi:10.1007/s10257-017-0338-y

Masayuki, M. (2016). *The Effects of Artificial Intelligence and Robotics on Business and Employment: Evidence from a survey on Japanese firms* (Discussion Paper Series No. 16-E-066). Research Institute of Economy, Trade and Industry (RIETI). https://www.rieti.go.jp/jp/publications/dp/16e066.pdf.

Molinillo, S., & Japutra, A. (2017). Organizational adoption of digital information and technology: a theoretical review. *The Bottom Line*, *30*(1), 33-46. doi:10.1108/BL-01-2017-0002

Nicholas-Donald, A., Mahmood, M. A., & Trevino, L. L. (2018). Does adoption of cloud computing matter? The economic worth of cloud computing implementation. *International Journal of Information Systems and Management*, *1*(4), 328-342. doi:10.1504/IJISAM.2018.094756

Nicoletti, G., von Rueden, C., & Andrews, D. (2020). Digital technology diffusion: A matter of capabilities, incentives or both? *European Economic Review*, *128*, 103513. doi:10.1016/j.euroecorev.2020.103513

Ohnemus, J., & Niebel, T. (2016). On the determinants of cloud computing adoption. In *27th European Regional Conference of the International Telecommunications Society (ITS): "The Evolution of the North-South Telecommunications Divide: The Role for Europe"*. https://hdl.handle.net/10419/148694.

Pellegrini, L., Campi, S., Locatelli, M., Pattini, G., Di Giuda, G. M., & Tagliabue, L. C. (2021). Corrigendum: Digital Transition and Waste Management in Architecture, Engineering, Construction, and Operations Industry. *Frontiers in Energy Research*, *9*, 634357. doi:10.3389/fenrg.2021.634357

Rammer, C., Czarnitzki, D., & Fernández, G. P. (2021). *Artificial intelligence and industrial innovation: Evidence from firm-level data* (Discussion Paper No. 21-036). ZEW - Centre for European Economic Research. doi:10.2139/ssrn.3829822

Rogers, E. M. (1995). *Diffusion of innovations* (5th ed.). Free Press, New York.

Tornatzky, L., & Fleischer, M. (1990). *The process of technology innovation.* D.C. Heath & Company, Lexington, MA. doi:10.1007/BF02371446

Wooldridge, J. M. (2007). *Econometric Analysis of Cross Section and Panel Data.* The MIT Press.

Xu, D., Guo, Y., & Huang, M. (2021). Can artificial intelligence improve firms' competitiveness during the COVID-19 pandemic: international evidence. *Emerging Markets Finance and Trade*, *57*(10), 2812-2825. doi:10.1080/1540496X.2021.1899911

Young, H. P. (2009). Innovation diffusion in heterogeneous populations: Contagion, social influence, and social learning. *American Economic Review*, *99*(5), 1899-1924. doi:10.1257/aer.99.5.1899

Zolas, N., Kroff, Z., Brynjolfsson, E., McElheran, K., Beede, D. N., Buffington, C., ... Dinlersoz, E. (2021). *Advanced technologies adoption and use by US firms: Evidence from the annual business survey* (Working Papers No. 28290). NBER. doi:10.3386/w28290