Ekonomi, Politika & Finans Araştırmaları Dergisi, 2026, 11(1): 179-199
Journal of Research in Economics, Politics & Finance, 2026, 11(1): 179-199
Araştırma Makalesi / Research Article, https://doi.org/10.30784/epfad.1814381

HOW DIGITALIZATION SHAPES EXPORT POTENTIAL: FIRM-LEVEL INSIGHTS FROM THE EU AND BEYOND

Dijitalleşme İhracat Potansiyelini Nasıl Şekillendiriyor: AB ve Ötesinden Firma Düzeyinde Bulgular

Özlem FİKİRLİ* **& Hasan ŞAHİN****

Keywords: Artificial Intelligence, Cloud Computing, Robotics, Exports, Digitalization.

JEL Codes: D22, D83, F14.

Abstract

The primary objective of this study is to examine the relationship between the adoption of advanced digital technologies, such as artificial intelligence (AI), and the probability of exporting, utilizing a probit model. The results indicate that the adoption of artificial intelligence, cloud computing, and robotics technologies is positively and statistically significantly associated with the likelihood of exporting. Big data analytics, smart devices, and blockchain technologies do not show a statistically significant association with firms' likelihood of exporting. The study investigates the relationship between specific digital technologies and export destinations as a secondary objective by applying a multivariate probit model, which accounts for potential correlations among the error terms across destination-specific export decisions. The findings show that artificial intelligence and smart devices are significantly associated with exports to EU countries. Cloud computing is significantly associated with export activities to all countries except China. Big data analytics is significantly associated with exports to non-EU countries. In contrast, blockchain technology does not exhibit a statistically significant relationship with export destinations. Robotics technologies exhibit a consistent and positive association with export participation across all export regions.

Anahtar Kelimeler: Yapay Zeka, Bulut Bilişim, Robotik, İhracat, Dijitalleşme.

JEL Kodları: D22, D83, F14.

Öz

Bu çalışmanın temel amacı, yapay zeka (YZ) gibi ileri dijital teknolojilerin benimsenmesi ile firmaların ihracat olasılığı arasındaki ilişkiyi probit modeli kullanarak incelemektir. Elde edilen bulgular, yapay zeka, bulut bilişim ve robotik teknolojilerinin benimsenmesinin ihracat yapma olasılığıyla istatistiksel olarak anlamlı ve pozitif bir ilişkiye sahip olduğunu göstermektedir. Büyük veri analitiği, akıllı cihazlar ve blokzinciri teknolojileri ise firmaların ihracat yapma olasılığıyla istatistiksel olarak anlamlı bir ilişki göstermemektedir. Çalışma, ikincil bir amaç olarak, belirli dijital teknolojilerin ihracat yapılan bölgelerle ilişkisini çok değişkenli probit modeli kullanarak analiz etmektedir. Bu yöntem, bölgeye özgü ihracat kararlarında hata terimleri arasındaki olası korelasyonları dikkate almaktadır. Bulgular, yapay zekâ ve akıllı cihazların AB ülkelerine yapılan ihracatla anlamlı biçimde ilişkili olduğunu göstermektedir. Bulut bilişim Çin hariç tüm ülkelere ihracat faaliyetleriyle istatistiksel olarak anlamlı biçimde ilişkilidir. Büyük veri analitiği, AB dışındaki ülkelere yönelik ihracatla anlamlı bir ilişki göstermektedir. Buna karşılık, blokzincir teknolojisinin ihracat bölgeleriyle istatistiksel olarak anlamlı bir ilişkisi bulunmamaktadır. Robotik teknolojiler ise tüm ihracat bölgelerinde ihracat katılımıyla tutarlı ve pozitif bir ilişki sergilemektedir.

* Asst. Prof. Dr., Bartın University, Faculty of Economics and Administrative Sciences, Department of Economics, Türkiye, ozlem_fikirli@hotmail.com (Corresponding Author)
** Prof. Dr., Ankara University, Faculty of Political Sciences, Department of Economics, Türkiye, hasansahin68@gmail.com

Received Date (Makale Geliş Tarihi): 31.10.2025 *Accepted Date (Makale Kabul Tarihi): 30.03.2026*

1. Introduction

"Industry 4.0," which emerged from advances in computer technologies, refers to the fourth industrial revolution and reflects the digitalization of economies, particularly in production and business models. Digitalization offers many opportunities, especially for improvements in knowledge, productivity, output, and quality. Many countries, led by Germany, have implemented national programs to capture these advantages immediately (Dalenogare et al., 2018).

The Digital Agenda for Europe, a key component of the Europe 2020 strategy, was announced by the Commission in 2010. The Commission has established the Digital Single Market Strategy under three main headings. The first aims to increase access to digital products, the second to foster conditions for digital networks and services, and the third to maximize the growth potential of digitalization (European Parliament, 2022). According to the European Investment Bank (2021) report, the EU should accelerate digital transformation to become a leader in digitalization and to seize the advantages it offers. Furthermore, although the number of firms adopting digital technologies is increasing, they require support to catch up with leading countries in digitalization, such as the United States of America (European Investment Bank, 2021). The report also notes that firms adopting digital technologies are more productive and anticipate greater future employment growth.

The diffusion of digital technologies has been transforming firms and entrepreneurship (Zhang et al., 2022), as well as society, networks, industries, governments, and markets. One of the critical areas affected by digital technologies is international trade. Digital technologies have improved international trade through various channels, including reducing trade costs, information asymmetries, and security risks; increasing productivity, knowledge, speed, and quality; and enhancing the global supply chain. Trade models with knowledge externalities, such as knowledge creation and knowledge diffusion, are best suited to explore the evolution of international trade through digital technologies (Goldfarb and Trefler, 2018).

There are a few applied studies examining the effects of advanced digital technologies, such as artificial intelligence, blockchain, or big data, on exports at the firm level (Yoon et al., 2020; Denicolai et al., 2021; Teruel et al., 2022). Although a growing body of literature examines the relationship between digital technologies and exports, this study contributes by offering a comprehensive analysis of how different types of advanced digital technologies are associated with export behavior. We also examine the relationship between digital technologies and export destinations.

The primary objective of this study is to examine the relationship between the diffusion of digital technologies and the likelihood of exporting. In the subsequent section, we review the literature on the link between advanced digital technologies and international trade. We briefly describe the data and estimation method. Next, we present and discuss the estimation results. Finally, we conclude with the limitations and suggestions for further research.

2. Related Literature

International trade theories have evolved and have become increasingly adept at explaining the complex structure of trade. Traditional trade theory is based on countries' characteristics and comparative advantages. In other words, the government is the fundamental unit of trade in the conventional approach. With the emergence of new trade theory in the 1980s, the basic unit of trade shifted from the country to the industry (Krugman, 1980; Helpman, 1981; Ethier, 1982; Helpman and Krugman, 1985). Firms are treated as consistent and representative in both traditional and new theories. Within the new trade theory that emerged at the beginning of the twenty-first century, homogeneous firms have been replaced by heterogeneous firms (Melitz, 2003). The basic unit of trade is now the firm, and differences between firms drive trade in the new trade theory. Thus, the new trade theory succeeds in revealing the diversity of firms observed in firm-level data and in explaining the complexities of international trade (Ciuriak et al., 2015; Ranjan and Raychaudhuri, 2016).

Firms' export behavior is explained by various variables in the literature. The following describes some standard variables used in the empirical literature and their impact on exports. One of the main focuses of studies is firm productivity. Firms with higher productivity export and further increase productivity through externalities of export activity, such as learning by exporting (Clerides et al., 1998; Girma et al., 2004). Although sales per employee do not reflect real value-added, they have been considered an indicator of productivity (Morbey and Reithner, 1990; Chevassus-Lozza et al., 2013), and a positive relationship is expected between sales per employee and exports.

Firm size is another characteristic that affects exports. Size provides insight into production scale, and larger firms are generally associated with higher productivity (Johansson, 2009; Gajewski and Tchorek, 2017). A firm's age (Hiep and Ohta, 2007; Ricci and Trionfetti, 2012), foreign ownership (Srinivasan and Archana, 2011; Gajewski and Tchorek, 2017), participation in an international group (Sterlacchini, 2001), and the characteristics of the regions where firms operate (Rodríguez-Pose et al., 2013; Huang et al., 2017) also determine exports. A positive relationship exists between productivity, size, foreign ownership, participation in an international group, and exports. Human capital is another variable that influences a firm's export behavior (Johansson, 2009; Amadu and Danquah, 2019; Rodríguez and Orellana, 2020). Moreover, human capital is linked to innovation activities, enhancing the firm's absorptive capacity and competitiveness, which positively affects exports (Fonseca et al., 2019; Rodríguez and Orellana, 2020).

Other key determinants of exports highlighted in the literature include knowledge creation and knowledge diffusion (Sterlacchini, 2001; Gourlay and Seaton, 2004; Tomiura, 2007; Aw et al., 2008; Harris and Moffat, 2011; Goldfarb and Trefler, 2018; Amadu and Danquah, 2019; Lejpras, 2019; Federici et al., 2020). Knowledge creation refers to innovation and innovation-related activities, such as research and development (R&D) expenditures and the number of R&D personnel. In contrast, knowledge diffusion refers to the adoption of new technologies and the transfer of knowledge through channels such as foreign investment. Both knowledge creation and diffusion lead to more efficient resource use and increased productivity. Therefore, there is a positive relationship between knowledge creation, knowledge diffusion, and exports.

Digital technologies reshape international trade and its structure (Bekkers et al., 2018). A significant development in this structural transformation is internet technologies, particularly e-commerce (Meltzer, 2016; Ciuriak and Ptashkina, 2018; Dethine et al., 2020). E-commerce provides numerous advantages, including increased supply chain efficiency, labor productivity, and reduced transaction costs. Advanced digital technologies, such as artificial intelligence and cloud computing, further extend and deepen the dimensions of structural transformation. For instance, robotics technology enhances production efficiency and lowers marginal costs. Thanks to big data analytics, access to knowledge is easier than before (Ferraris et al., 2019), and with cloud computing, computing and storage costs for data are diminished, eliminating the need for hardware (Nicholas-Donald et al., 2018). Therefore, the diffusion of digital technologies leads to changes in production processes, organizational structures, and marketing activities.

2.1. Artificial Intelligence

Artificial intelligence (AI) is an information technology method that enables machines to understand, assess, learn, predict, and make decisions in real and virtual environments (Baruffaldi et al., 2020). Adopting AI offers firms many benefits, including data collection, evaluation, decision-making, economies of scale, and resource efficiency (Von Krogh, 2018). Furthermore, adopting AI boosts innovation activities (Rammer et al., 2021) and revenues (Xu et al., 2021). However, despite its opportunities and accelerated diffusion, few applied studies have examined its economic impacts (Giczy et al., 2022).

The effects of AI adoption extend beyond firms to the structure of international trade (Goldfarb and Trefler, 2018). Goldfarb and Trefler (2018) emphasize that trade models incorporating knowledge externalities, particularly scale, knowledge creation, and knowledge diffusion, are best suited to explaining AI's impact on trade patterns. Few applied studies demonstrate a positive relationship between AI and exports (Denicolai et al., 2021).

2.2. Cloud Computing

Cloud computing, which transforms the structure of information and communication technologies (ICT), is an innovative pay-as-you-go application framework (Son et al., 2011). It offers firms access to ICT capabilities such as storage, software, and processing (OECD, 2015; van Ark, 2016; DeStefano et al., 2020). Cloud computing reduces fixed ICT costs and converts them into marginal costs (Schniederjans and Hales, 2016). Thus, the firm-level effects of cloud computing diffusion are evident in increased savings. Literature indicates that cloud computing adoption enhances firms' economic performance (Schniederjans and Hales, 2016), trading volume, market value (Son et al., 2011), employment, and revenue (DeStefano et al., 2020). Conversely, Etro (2010) argues that the diffusion of cloud computing decreases markups and creates new jobs in EU countries. Moreover, Kshetri (2011) notes that the diffusion of cloud computing boosts productivity, efficiency, and innovation in developing economies. Although research has explored the economic and organizational impacts of cloud computing, its connection to firms’ export behavior has received comparatively limited attention in empirical research. However, a positive association between cloud computing adoption and exports may be expected.

2.3. Big Data Analytics

Big data analytics can be viewed as a data mining technique or as a process for generating meaningful information and knowledge from big data (Chen et al., 2012). It requires the characteristics of data's velocity, volume, value, variety, and veracity, collectively represented by the 5Vs (Gupta et al., 2018). Firms increase their knowledge stocks through big data analytics, gaining insights into consumer preferences and behaviors, improving products, and understanding other firms and markets. This increase in knowledge stocks enables firms to make better decisions and gain competitive advantages. Furthermore, firms that have adopted big data analytics have experienced enhanced performance (Müller et al., 2018; Ferraris et al., 2019), innovation performance (Ghasemaghaei and Calic, 2020), innovation activities, and innovation success (Niebel et al., 2019).

Big data analytics also enables firms to analyze and adapt to foreign markets (Cheng et al., 2020). Cheng et al. (2020) report that big data analytics has accelerated internationalization, as measured by indicators such as exports. Moreover, Wang (2020) notes that export financing costs can be reduced through big data analytics.

2.4. Robotics

The International Federation of Robotics (IFR) classifies robots into industrial and service robots. IFR adopts the International Organization for Standardization (ISO) definition of industrial robots and highlights their "automatically controlled, programmable, multipurpose and 3+ axes" features (IFR, 2020). Service robots are defined as robots that perform personal or domestic tasks outside the industrial sector (IFR, 2020). The accelerating adoption of robotics has attracted significant research attention, resulting in a broader literature on other digital technologies. Studies in this literature particularly focus on the effects of robotics on labor and productivity (Graetz and Michaels, 2018; Compagnucci et al., 2019; Acemoglu and Restrepo, 2020; Kromann et al., 2020; Fu et al., 2021). The literature establishes that the diffusion of robotics increases both labor productivity and total factor productivity (Graetz and Michaels, 2018; Jungmittag and Pesole, 2019; Kromann et al., 2020). On the other hand, recent studies note both conditional and unconditional convergence of robot densities across EU countries (Jungmittag, 2021).

Ballestar et al. (2020) argue that robotics and productivity are positively related at the firm level. When considering the correlation between robotics and productivity, production and trade patterns are expected to evolve. On the trade side, Alguacil Marí et al. (2020) reveal that the diffusion of robotics has increased firms' export probability, export sales, and the share of exports in output. DeStefano and Timmis (2021) also note that the diffusion of robotics has improved the quality of exported products.

2.5. Smart Devices

Smart devices are machines with intelligent capabilities, such as smart sensors and smart thermostats (European Commission, 2020). The diffusion of smart devices is discussed across various topics, including smart manufacturing, smart cities, smart grids, smart businesses, and the Internet of Things (Georgakopoulos and Jayaraman, 2016; Kabalci, 2016; Mendling et al., 2017; Desdemoustier et al., 2019; Lu et al., 2020). Smart devices offer firms numerous opportunities, enhancing production quality, product lifespan, production efficiency, productivity, and competitive advantage while minimizing security risks and downtime (Conway, 2016; Zhong et al., 2017). Empirical evidence on the relationship between the adoption of smart devices and exports remains limited. However, firms that adopt smart devices are expected to be more likely to export, particularly because of competitive advantage and productivity gains.

2.6. Blockchain

Blockchain is a decentralized global platform that stores transaction records and is characterized by immutability, trust, and transparency (Nakamoto, 2008; Swan, 2015; Tapscott and Tapscott, 2016; Leloup, 2017; Belu, 2019). Blockchain technology is expected to transform traditional international trade, particularly by reducing trade costs, addressing information asymmetries in the flow of goods, and increasing speed and efficiency (De Caria, 2017; Kshetri, 2019; McDaniel and Norberg, 2019; Kimani et al., 2020). Limited studies examine the diffusion of blockchain technologies at the firm level (Yoon et al., 2020; Balci and Surucu Balci, 2021). Balci and Surucu Balci (2021) identify barriers to adoption and the key stakeholders that influence it in international trade. According to the authors, the main barriers are a lack of stakeholder support, insufficient technological knowledge, and inadequate government regulations. On the other hand, Yoon et al. (2020) report that the diffusion of blockchain has resulted in increased maritime transport and decreased air transport.

3. Data and Method

Flash Eurobarometer surveys, initiated on a small scale by the European Commission in the late 1980s, have since covered a wide range of topics, from gender inequalities to the effects of drugs. Data and documents are available in an online database. The countries surveyed vary by survey scope. This study uses the Flash Eurobarometer 486 "SMEs, Start-ups, Scale-ups, and Entrepreneurship" survey (2020). This survey includes businesses located in the EU, Bosnia and Herzegovina, Brazil, Canada, Iceland, Japan, Kosovo, North Macedonia, Norway, Serbia, the United Kingdom, Turkey, and the United States, operating in the manufacturing (Nace category C), retail (Nace category G), services (Nace categories H, I, J, K, L, M, N, P, Q, R), and industry (Nace categories B, D, E, F) sectors (European Commission, 2020).

The relationship between the diffusion of digital technologies and exports is explored using Equation 1, which is based on new trade theory. In the equation, y, α, β, and ε represent a dependent variable, a constant term, unknown parameters, and an error term, respectively.

$$\begin{aligned} y_i = \alpha_i &+ \beta_1 AI_i + \beta_2 CLOUD_i + \beta_3 BDA_i + \beta_4 ROBOT_i + \beta_5 SMD_i + \beta_6 BLOCK_i \\ &+ \beta_7 SALES_i + \beta_8 AGE_i + \beta_9 AGE2_i + \beta_{10} LOGEMP_i + \beta_{11} BNDEU_i \\ &+ \beta_{12} BNDOTH_i + \beta_{13} GLOBAL_i + \beta_{14} GROUP_i + \beta_{15} PATENT_i \\ &+ \beta_{16} INNOVA_i + \beta_{17} HUMAN_i + \varepsilon_i \end{aligned} \tag{1}$$

The dependent variable indicates whether the firm engages in export activity. Since different foreign markets entail varying entry costs (Damijan et al., 2004), the firms' export activities are examined using four binary dependent variables. We explore the relationship between the diffusion of digital technologies and firms' export behavior, including exports to EU countries, China, and other countries outside the EU and China.

The independent variables include firm characteristics, knowledge creation, and knowledge diffusion. Variables capturing firm heterogeneity include sales, firm age, the square of age to capture nonlinear effects, the logarithm of employees, geographic location, ownership type, participation in a global value chain, and human capital. Knowledge creation is indicated by the firm's innovative activities and patent applications. Finally, knowledge diffusion, the primary focus of the study, is represented by the adoption of digital technologies. All models include country and sector fixed effects to control for unobserved heterogeneity across countries and industries. Country and sector fixed effects are implemented using a full set of dummy variables, with one category omitted in each case to avoid multicollinearity. These controls are included in all estimated equations. Variable descriptions and descriptive statistics are summarized in Table 1.

Table 1. Description and Descriptive Statistics of The Variables

Dependent Variables	**Description**	**% (Percentage)**			
EXPORT	Operates in national boundaries=0, otherwise=1	34.960%			
EEU	Exports to EU countries=1, otherwise=0	31.14%			
ECHN	Exports to China=1, otherwise=0	4.901%			
EOTHER	Exports to other countries outside of the EU and China=1, otherwise=0	12.616%			
Digitalization Variables					
AI	Adopts artificial intelligence=1, otherwise=0	9.056%			
CLOUD	Adopts cloud computing=1, otherwise=0	53.268%			
BDA	Adopts big data analytics=1, otherwise=0	16.187%			
ROBOT	Adopts robotics=1, otherwise=0	9.944%			
SMD	Adopts smart devices=1, otherwise=0	30.351%			
BLOCK	Adopts blockchain=1, otherwise=0	3.722%			
Independent Variables					
BNDEU	Located near a border with an EU country=1, otherwise=0	9.251%			
BNDOTH	Located near a border with a country outside of the EU=1, otherwise=0	3.365%			
GLOBAL	Part of a global value chain=1, otherwise=0	11.675%			
GROUP	Ownership of national or international group=1, otherwise=0	9.349%			
PATENT	Has a patent or patent application=1, otherwise=0	7.661%			
INNOVA	Introduced any innovation during the past 12 months=1, otherwise=0	65.105%			
Independent Variables					
Variables	**Description**	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
SALES	Standardized sales per employee	-0.001	0.992	-0.916	18.398
AGE	Years from the first registered	25.078	22.039	0	170
AGE2	Square of years from the first registered	1114.559	2470.126	0	28900
LOGEMP	Logarithm of employees	2.399	1.613	0	9.105
HUMAN	Availability of staff with the right skills (Very poor=1, Fairly poor=2, Fairly good=3, Very good=4)	2.618	0.857	1	4
Number of Observations: 9242					

Source: Author(s). The SALES variable is standardized within each country by subtracting the mean and dividing by the standard deviation. Descriptive statistics are reported without sampling weights because the main empirical analysis relies on an unweighted multivariate probit model.

We have four binary dependent variables indicating whether a firm exports, exports to the EU, exports to China, or exports to other countries outside the EU and China. Using a probit model estimated with survey weights, we examine the relationship between the diffusion of digital technology and firms' export behavior. Furthermore, we analyze the association between digital technology diffusion and export status by destination using a multivariate probit model that appropriately accounts for potential correlations among the error terms across export destinations.

The multivariate probit model is estimated using the full sample of firms. An alternative modeling strategy would use a sequential decision framework, in which firms first decide whether to export and then choose their export destinations. Such a structure typically requires two-stage sample selection models. While this approach is appropriate when destination choices are mutually exclusive and conditional on export participation, it is less suitable in the present context. Firms in our sample may export to multiple destinations simultaneously, implying that destination choices are not mutually exclusive and are likely influenced by common observed and unobserved factors. As a result, export decisions across destinations may be correlated. To explicitly account for these interdependencies and shared determinants, we adopt a multivariate probit framework, which allows for correlated error terms across destination-specific export equations. This modeling choice enables a joint analysis of export destination decisions without imposing a restrictive sequential structure.

Table 2. Characteristics of the Exporter Firms

Independent Binary Variables	**Exporter Firms % (Percentage)**			
AI	13.309%			
CLOUD	61.250%			
BDA	21.479%			
ROBOT	17.394%			
SMD	38.007%			
BLOCK	5.107%			
BNDEU	13.309%			
BNDOTH	3.621%			
GLOBAL	17.858%			
GROUP	14.392%			
PATENT	13.989%			
INNOVA	74.249%			
Number of Observations	Exporter Firms: 3231			
Independent (Continuous and Ordinal) Variables	**Mean**	**Std. Deviation**	**Minimum**	**Maximum**
SALES	0.046	1.058	-0.760	16.268
AGE	26.590	22.760	0	170
AGE2	1224.879	2537.208	0	28900
LOGEMP	2.859	1.713	0	8.612
HUMAN	2.596	0.835	1	4

Note: The values reported in the table are averages. The SALES variable is standardized by subtracting the country-specific mean and dividing by the country-specific standard deviation. Descriptive statistics are reported without sampling weights, as the main empirical analysis relies on an unweighted multivariate probit model.

Exporter and non-exporter firms differ in their characteristics (Bernard et al., 2007). We summarize these characteristics in Table 2 and Table 3. According to the tables, exporter firms are more likely to adopt digital technologies than non-exporter firms. Additionally, exporter firms are older, larger, and have higher sales per employee than non-exporter firms. These features align with the literature. Moreover, if sales are taken as a proxy for productivity, exporter firms are more productive than non-exporter firms, which aligns with the literature.

As a robustness check, we additionally estimate separate probit models for each export destination. These probit models use sampling weights provided by the Flash Eurobarometer to ensure representativeness. However, survey weights could not be incorporated into the multivariate probit estimations under the estimation procedure used in this study. Therefore, the main multivariate probit specification is estimated without weighting.

Table 3. Characteristics of Non-exporter Firms

Independent Binary Variables	**Non-Exporter Firms % (Percentage)**			
AI	6.771%			
CLOUD	48.977%			
BDA	13.342%			
ROBOT	5.939%			
SMD	26.235%			
BLOCK	2.978%			
BNDEU	7.070%			
BNDOTH	3.227%			
GLOBAL	8.351%			
GROUP	6.638%			
PATENT	4.259%			
INNOVA	60.190%			
Number of Observations	Non-Exporter Firms: 6011			
Independent (Continuous and Ordinal) Variables	**Mean**	**Std. Deviation**	**Minimum**	**Maximum**
SALES	-0.026	0.953	-0.916	18.398
AGE	24.266	21.599	0	170
AGE2	1055.261	2431.45	0	28900
LOGEMP	2.152	1.500	0	9.105
HUMAN	2.630	0.869	1	4

Note: The values reported in the table are averages. The SALES variable is standardized by subtracting the country-specific mean and dividing by the country-specific standard deviation. Descriptive statistics are reported without sampling weights, as the main empirical analysis relies on an unweighted multivariate probit model.

4. Results

The probit estimation results are presented in Table 4. The results are consistent with the existing literature and align with expectations. Several firm-level characteristics, including sales, firm size, geographic location, participation in global value chains, patent applications, and innovation activities, are positively and significantly associated with export activity. However, a statistically significant negative relationship is observed between firm age and exports (Love et al., 2016). This suggests that older firms are more likely to focus on domestic markets rather than on exports. In addition, group ownership shows a weak positive association with exports at the 10% significance level.

Regarding digital technologies, there is a positive and statistically significant relationship between exports and the adoption of artificial intelligence, cloud computing, and robotics at the 5% level of significance. The findings of this study support the view that advanced digital technologies are positively associated with exports, as highlighted in previous studies (Denicolai et al., 2021; Alguacil Marí et al., 2020).

Although the literature highlights the potential positive impact of big data analytics and blockchain technologies on export performance (Cheng et al., 2020; Wang, 2020; Yoon et al., 2020), this study does not find a statistically significant relationship between these technologies and firms' export activities. Similarly, smart devices are not significantly associated with export activity. The primary expected contribution of these technologies to export performance is the reduction of financial costs associated with international trade. However, the sample examined in this study predominantly consists of firms located in EU countries, where institutional mechanisms already exist to facilitate intra-union trade and provide financial support. Therefore, the absence of a significant relationship in this study may be attributed to the established systems within the EU, which may diminish the marginal benefits of adopting these technologies in export processes.

Table 4. Probit Estimation Results

Independent Variables	**Dependent Variable: EXPORT** (Operates in national boundaries=0, otherwise=1)
AI	0.235*** (0.068)
CLOUD	0.217*** (0.039)
BDA	0.080 (0.055)
ROBOT	0.198*** (0.072)
SMD	0.050 (0.043)
BLOCK	0.013 (0.105)
SALES	0.072*** (0.017)
AGE	-0.005** (0.002)
AGE2	0.00001 (0.00002)
LOGEMP	0.121*** (0.015)
BNDEU	0.247*** (0.059)
BNDOTH	-0.048 (0.109)
GLOBAL	0.300*** (0.063)
GROUP	0.125* (0.073)
PATENT	0.511*** (0.078)
INNOVA	0.243*** (0.039)
HUMAN	-0.023 (0.021)
Constant	-1.314*** (0.300)
Number of Observations: 9242	
F(70, 9172) = 16.70	
Prob > F = 0.0000	

Note: Values in the table are coefficients, and those in parentheses are linearized standard errors. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Country and sector fixed effects are included. The model is estimated with survey-weighted probit. Overall model significance is assessed using the design-based F-statistic.

The marginal effects are presented in Table 5. The adoption of artificial intelligence, cloud computing, and robotics is associated with higher predicted probabilities of exporting, corresponding to approximately 8, 6.9, and 6.7 percentage points, respectively. This finding aligns with the widely recognized efficiency gains of these technologies, including cost reductions, time savings, and optimal resource utilization. These advantages are consistent with greater competitiveness and a higher likelihood of participation in international markets. No statistically significant marginal effects are found for big data analytics, smart devices, or blockchain adoption.

Table 5. Marginal Effects

Independent Variables	**Dependent Variable: EXPORT** (Operates in national boundaries=0, otherwise=1)
AI	0.080**(0.024)
CLOUD	0.069**(0.013)
BDA	0.026 (0.018)
ROBOT	0.067**(0.025)
SMD	0.016(0.014)
BLOCK	0.004(0.034)

Note: Reported coefficients are average marginal effects obtained from a survey-weighted probit model. Robust standard errors are in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

The relationship between digital technologies and exports by destination is examined using the multivariate probit method. The estimation results are presented in Table 6. Table 6 shows that the estimated correlation coefficients of the error terms (rho21, rho31, and rho32) are statistically significant, indicating interdependence among the export destinations. Therefore, estimating the equations simultaneously with the multivariate probit approach is more appropriate than conducting separate univariate analyses, as it accounts for potential correlations in unobserved factors across export markets.

The determinants of exports appear broadly consistent across export destinations. Firm-level characteristics, including total sales, the logarithm of the number of employees, ownership structure, participation in global value chains, patent applications, and innovation activities, are significantly and positively associated with exports to all markets. However, the association between geographic location and exports varies depending on whether a firm is near EU countries. Specifically, being a bordering EU country is positively associated with exports to the EU. There is also weak evidence at the 10% significance level that proximity to EU borders is positively related to exports to other countries, whereas proximity to non-EU borders shows weak evidence of a negative association with exports to EU markets. Additionally, firm age, its squared term, and proximity to other countries are statistically insignificant for all export destinations. Finally, the availability of skilled personnel, representing the firm’s human capital, is significantly associated with exports to China only, while weak evidence at the 10% significance level suggests a negative association with exports to EU countries.

According to Table 6, blockchain technology is not statistically significantly associated with exports, regardless of the export destination. This finding aligns with the export determinants reported in Table 4. There is a statistically significant positive relationship at the 1% level between artificial intelligence adoption and exports to EU countries. Cloud computing is significantly associated with exports to all countries except China. Big data analytics is significantly associated with exports to all countries outside the EU. Robotics is consistently and positively associated with exports across all destinations, with a consistent and significant positive association at the 1% level. Finally, the adoption of smart devices is significantly associated with exports, specifically to EU countries.

The relationship between digital technologies and exports varies by export destination. The adoption of artificial intelligence, cloud computing, robotics, and smart devices is primarily associated with exports to EU countries. In contrast, exports to China are more strongly associated with big data analytics and robotics. For exports to countries outside the EU and China, the main technologies are cloud computing, big data analytics, and robotics.

Table 6 also presents results from independent survey-weighted probit estimations as robustness checks. Because the multivariate probit and weighted probit models use different estimation frameworks and assumptions, some variation in coefficient magnitudes or significance levels is expected. Nevertheless, the main findings are generally consistent across both methods, with no major differences evident in Table 6. This overall agreement reinforces the robustness and internal consistency of the results.

Table 6. Results of Multivariate Probit Estimation and Probit Estimations (Coefficients)

	Multivariate Probit			Probit		
Independent Variables	**EEU**	**ECHN**	**EOTHER**	**EEU**	**ECHN**	**EOTHER**
AI	0.174***	0.095	0.111	0.160**	0.003	0.110
	(0.063)	(0.066)	(0.073)	(0.070)	(0.119)	(0.082)
CLOUD	0.156***	0.120	0.183***	0.197***	0.151**	0.215***
	(0.038)	(0.081)	(0.037)	(0.041)	(0.075)	(0.053)
BDA	0.063	0.133**	0.098**	0.052	0.164*	0.128*
	(0.039)	(0.053)	(0.049)	(0.056)	(0.091)	(0.065)
ROBOT	0.230***	0.314***	0.233***	0.210***	0.241**	0.250***
	(0.056)	(0.075)	(0.060)	(0.070)	(0.098)	(0.082)
SMD	0.059**	0.059	0.061	0.084*	0.045	0.035
	(0.029)	(0.048)	(0.041)	(0.044)	(0.071)	(0.056)
BLOCK	-0.107	0.026	-0.134	-0.041	0.003	-0.154
	(0.083)	(0.111)	(0.095)	(0.103)	(0.159)	(0.124)
SALES	0.062***	0.076***	0.086***	0.055***	0.089***	0.082***
	(0.014)	(0.018)	(0.019)	(0.016)	(0.022)	(0.019)
AGE	-0.002	-0.000	0.001	-0.004*	-0.002	-0.001
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
AGE2	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LOGEMP	0.115***	0.098***	0.111***	0.116***	0.118***	0.118***
	(0.012)	(0.014)	(0.017)	(0.016)	(0.024)	(0.018)
BNDEU	0.278***	0.048	0.098*	0.279***	0.063	0.023
	(0.054)	(0.084)	(0.052)	(0.059)	(0.105)	(0.082)
BNDOTH	-0.175*	0.027	0.125	-0.276**	0.063	0.251*
	(0.105)	(0.152)	(0.096)	(0.122)	(0.190)	(0.139)
GLOBAL	0.291***	0.351***	0.314***	0.295***	0.321***	0.335***
	(0.050)	(0.058)	(0.055)	(0.064)	(0.095)	(0.075)
GROUP	0.195***	0.239***	0.210***	0.189**	0.190*	0.026
	(0.057)	(0.060)	(0.036)	(0.074)	(0.099)	(0.078)
PATENT	0.571***	0.497***	0.528***	0.486***	0.440***	0.499***
	(0.083)	(0.073)	(0.067)	(0.080)	(0.099)	(0.082)
INNOVA	0.243***	0.167***	0.215***	0.248***	0.203***	0.222***
	(0.036)	(0.058)	(0.043)	(0.041)	(0.074)	(0.055)
HUMAN	-0.028*	0.077***	-0.008	-0.033	0.072*	0.005
	(0.017)	(0.027)	(0.024)	(0.022)	(0.040)	(0.029)
Constant	-1.388***	-2.859***	-1.773***	-1.491***	-3.172***	-1.733***
	(0.259)	(0.524)	(0.236)	(0.379)	(0.483)	(0.329)
rho 21		0.607***		-	-	-
		(0.029)				
rho 31		0.654***		-	-	-
		(0.025)				
rho 32		0.684***		-	-	-
		(0.020)				
Likelihood ratio test (H0: rho21 = rho31 = rho32 = 0)	Chi-Square (3) = 1621.75 Prob = 0.0000			F(70,9172)= 15.71 Prob > F= 0.0000	F(66,8862)=6.83 Prob > F = 0.0000	F(69,9124)=10.85 Prob > F= 0.0000

Note: Values in tables are coefficients, and those in parentheses are standard errors (linearized for weighted estimates). *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. All specifications include country and sector fixed effects. Columns 1, 2, and 3 report unweighted estimates, while columns 4, 5, and 6 are weighted using the Flash Eurobarometer sampling weight.

At the same time, it should be noted that the empirical framework employed in this study does not explicitly resolve potential endogeneity concerns. To address this issue to the extent permitted by the data, a set of robustness checks based on alternative estimation strategies has been implemented, in line with the reviewer's suggestions. These additional estimates help mitigate potential endogeneity concerns and strengthen confidence in the reported associations. Nonetheless, the findings should not be interpreted as establishing causal effects. Rather, they provide evidence on the direction in which adaptation to digital technologies may be associated with firms' export probabilities, reflecting conditional relationships rather than definitive causal links.

5. Discussion and Conclusion

Digitalization offers numerous advantages, including increased efficiency, reduced financial and time-related costs, enhanced operational effectiveness, greater product diversity and quality, and waste reduction. These benefits have accelerated the global race toward digital transformation. In line with national digital transformation roadmaps, a comprehensive shift is occurring across economic markets and societal structures. Digital transformation also affects international trade, leading to the restructuring of global trade networks. As the structure of global trade continues to evolve, integration into this new order largely depends on firms' ability to keep pace with digital transformation. The presence of globally competitive large firms is essential for countries to achieve high levels of welfare.

Digital technologies encompass a wide range of tools and systems, from foundational technologies like the internet to advanced technologies such as blockchain. Accordingly, the potential benefits and strategic advantages of digital technologies vary by type. In the context of international trade, the expected contributions of digital technologies also differ. For instance, artificial intelligence is regarded as a driving force in foreign trade because it supports innovation, enhances market analysis, and accelerates and improves decision-making, thereby providing firms with a competitive edge. Conversely, blockchain is anticipated to support international trade through distinct channels, such as reducing financial transaction costs, minimizing time costs, and facilitating supply chain traceability. Therefore, the contribution of digital technologies to a firm's trade performance depends on the specific technology adopted.

This study focuses on six digital technologies: artificial intelligence, cloud computing, big data analytics, robotics, smart devices, and blockchain. The limitations of the available dataset guided the selection of these technologies. Overall, the findings indicate a positive relationship between firms' adoption of digital technologies and exports. However, the nature and strength of this relationship vary by the type of digital technology.

Artificial intelligence, cloud computing, and robotics are consistently and positively associated with exports. As shown in Tables 2 and 3, an examination of the characteristics of exporting and non-exporting firms reveals that exporters tend to adopt these technologies more extensively. Technologies that dominate production automation, such as robotics, primarily offer cost advantages. Because production costs are among the most critical determinants of international trade, these technologies are associated with greater competitiveness in foreign markets.

Moreover, firms targeting multiple export destinations often face the challenge of storing and managing larger volumes of information, including official export documentation, customer portfolios, and market analyses. In this context, cloud computing reduces data storage costs and improves operational efficiency. Additionally, artificial intelligence offers a wide range of benefits, from supporting the development of innovative products to enabling faster, more responsive decision-making that aligns with market needs.

On the other hand, big data analytics and blockchain technologies do not play a statistically significant role in firms' export performance. According to the firm characteristics reported in Tables 2 and 3, only 5% of exporting firms and 3% of non-exporting firms have adopted blockchain technology. Because blockchain is relatively new compared with other digital technologies, firms may still have limited knowledge and experience with its effective use. This lack of familiarity may help explain its low adoption rate and limit its application in export processes.

Regarding big data analytics, Tables 2 and 3 show that 21% of exporting firms and 13% of non-exporting firms have adopted this technology. Although this indicates a notable difference in adoption rates between exporters and non-exporters, big data analytics is not statistically significantly associated with the likelihood of exporting. Technologies such as big data analytics and blockchain are expected to primarily reduce the financial costs of international trade. However, because the data set used in this study consists mainly of firms located in EU countries, where firms already benefit from institutional and financial advantages due to membership in the same economic bloc, the additional contribution of these technologies may be less visible in this context.

The diffusion of digital technologies is associated with improvements in export performance. The adoption of these technologies is associated with a higher likelihood that firms engage in exports. Therefore, policies that facilitate the adoption of core digital technologies may warrant consideration, particularly in export-oriented strategies. Implementing policies that facilitate the transition to these technologies is urgently needed to ensure that countries can secure and strengthen their position within the evolving global trade network.

At the same time, the practical applications and effective use cases of big data analytics and blockchain technologies within firms should be further explored. Research findings should be shared with firms to increase awareness and inform them about these technologies. The advantages of these tools largely depend on firms' ability to use them effectively in their operations.

On the other hand, the digital technologies associated with exports vary by destination. Artificial intelligence and smart devices are strongly associated with exports to EU countries. Cloud computing is significantly associated with exports to all countries except China. The adoption of big data analytics is positively associated with exports to all countries outside the EU. In contrast, blockchain technology shows no statistically significant relationship with export activity. Robotics is consistently associated with exports across all destinations.

To summarize, artificial intelligence, cloud computing, robotics, and smart device technologies are strongly associated with exports to EU countries. As previously discussed, artificial intelligence is strongly associated with innovation-related outcomes, while robotics is primarily associated with cost minimization, productivity gains, and more efficient resource use.

These complementary characteristics are linked to greater competitiveness and a higher likelihood of entry into international markets. Adopting these technologies should be a strategic priority for firms targeting EU markets. Similarly, countries aiming to strengthen their export ties with the EU should accelerate the digital transformation of their firms, particularly in these critical technological areas.

For firms aiming to export to EU countries and for countries seeking to increase their exports to the EU, artificial intelligence, cloud computing, robotics, and smart devices may be strategic priorities for firms targeting EU markets. While the diffusion of these technologies within firms should be supported, efforts must also provide guidance and capacity-building to ensure their effective use. Otherwise, mere adoption of these technologies may not confer a competitive advantage over rival firms, and it may be difficult for new entrants to access and establish a foothold in international markets.

On the other hand, exports to China appear to be more closely associated with automation-related technologies. Robotics and big data analytics are key factors associated with exports to China. As one of the leading robotics countries, China holds a significant position in global trade due to its low-cost production structure. This cost advantage represents a significant barrier to entry for firms seeking to access the Chinese market. The findings of this study suggest that the likelihood of exporting to China is positively associated with the adoption of digital technologies, which may offer substantial cost advantages. While robotics, commonly referred to as the automation of production structures, may have adverse effects on employment, the results also suggest that automation technologies are positively associated with production and employment growth through the export channel. Therefore, when evaluating the role of automation technologies in relation to employment, it is essential to consider their potential positive associations via export activity.

The adoption of cloud computing, big data analytics, and robotics is significantly associated with exports to countries outside the EU and China. A higher likelihood of exporting to these countries is associated not only with the adoption of cost-reducing digital technologies, such as robotics, but also with the adoption of data-driven solutions, including cloud computing and big data analytics. Thus, exports to these destinations are associated with the adoption of diverse digital technologies that serve different purposes and offer distinct advantages. It is essential to support firms in their digital transformation and to prioritize those with advanced digital capabilities in export promotion policies.

Furthermore, the statistical significance of all estimated correlation coefficients across export destinations indicates that firms' decisions to enter international markets are interconnected rather than independent. This pattern likely reflects multiple factors, including multi-market strategies, serving several regions simultaneously, accumulated export experience, and other unobserved influences that collectively shape export behavior. Therefore, significant correlations across destinations highlight a more cohesive, interconnected process of internationalization, underscoring the importance of the multivariate probit model for capturing these linked export decisions.

One limitation of this study is the limited availability of data. Because the analysis relies on cross-sectional data, it is impossible to estimate time-lagged effects associated with the diffusion of digital technologies. Future research, especially studies using panel data, will be crucial to further substantiate the connection between digital technology diffusion and exports and to investigate the temporal dynamics of the diffusion process.

Moreover, digital technologies have a wide range of applications. Due to limitations in the dataset, this study could not classify digital technologies by their specific areas of use or intended functions. Future studies may benefit from a more detailed classification of digital technologies by usage type and application domain to better understand their differential impacts on export performance.

Declaration of Research and Publication Ethics
This study, which does not require ethics committee approval or specific legal permission, complies with research and publication ethics.

Researcher's Contribution Rate Statement
The authors declare that they have contributed equally to the article.

Declaration of Researcher's Conflict of Interest
The authors declare that they have no conflict of interest.

Declaration of Artificial Intelligence Usage
The authors did not use any artificial intelligence tools during the preparation of this manuscript.

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