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Artificial intelligence enabling factors and foreign direct investment attraction: econometric evidence from Estonia's digital innovation ecosystem (2005–2024)

Czynniki umożliwiające
rozwój sztucznej inteligencji
a przyciąganie bezpośrednich
inwestycji zagranicznych: dowody
ekonometryczne z estońskiego
ekosystemu innowacji cyfrowych
(2005–2024)

Keywords:

Artificial intelligence,
AI readiness, digital
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investment, technological
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model

Abstract: This study aims to examine the role of artificial intelligence (AI) enabling factors in enhancing Estonia's capacity to attract foreign direct investment (FDI) during the period 2005–2024, focusing on digital readiness and technological innovation indicators. Due to the absence of consistent long-term data on direct AI adoption, the study employs proxy indicators, including digital infrastructure, research and development (R&D) expenditure, and patent activity, as key components of AI-related capabilities. The ARDL approach is applied to investigate the short- and long-run relationships among the variables. The findings indicate that strengthening digital and innovation ecosystems contributes significantly to improving Estonia's attractiveness to foreign investors. The Estonian experience demonstrates that investments in digital infrastructure, human capital, and innovation capabilities constitute strategic foundations for integrating into the global digital economy and enhancing investment competitiveness.

Słowa kluczowe:

sztuczna inteligencja, gotowość na rozwój sztucznej inteligencji (AI readiness), transformacja cyfrowa, bezpośrednie inwestycje zagraniczne, innowacje technologiczne, infrastruktura cyfrowa, badania i rozwój (B+R), Estonia, model ARDL

Streszczenie: Celem badania jest analiza roli czynników umożliwiających rozwój sztucznej inteligencji (AI) w zwiększaniu zdolności Estonii do przyciągania bezpośrednich inwestycji zagranicznych (BIZ) w latach 2005–2024, ze szczególnym uwzględnieniem wskaźników gotowości cyfrowej i innowacji technologicznych. Ze względu na brak spójnych długoterminowych danych dotyczących bezpośredniego wdrażania sztucznej inteligencji, w badaniu zastosowano zmienne zastępcze obejmujące infrastrukturę cyfrową, wydatki na badania i rozwój (B+R) oraz aktywność patentową jako kluczowe elementy zdolności związanych z AI. Do analizy relacji krótko- i długookresowych między zmiennymi wykorzystano metodę ARDL. Wyniki wskazują, że rozwój ekosystemu cyfrowego i innowacyjnego istotnie przyczynia się do zwiększenia atrakcyjności Estonii dla inwestorów zagranicznych. Doświadczenia Estonii pokazują, że inwestycje w infrastrukturę cyfrową, kapitał ludzki oraz zdolności innowacyjne stanowią strategiczne podstawy integracji z globalną gospodarką cyfrową i wzmacniania konkurencyjności inwestycyjnej.

JEL:

F21, O32, O33, O38, C22

Introduction

Over the past two decades, the global economy has undergone profound transformations driven by rapid technological advancement, digitalization, and the growing importance of knowledge-based activities [Zhang et al., 2024]. In this context, Artificial Intelligence (AI) has emerged as one of the most influential technologies shaping economic development and competitiveness [Zandieh, 2026]. By enhancing productivity, improving decision-making processes, supporting innovation, and optimizing resource allocation, AI has become a key driver of digital transformation across various economic sectors [Raina et al., 2026]. As a result, countries' technological and digital capabilities are increasingly recognized as critical determinants of their ability to compete in the global economy and attract high-value economic activities [Jiao et al., 2025].

At the same time, Foreign Direct Investment (FDI) continues to play a vital role in promoting economic growth and development by facilitating capital accumulation, technology transfer, knowledge spillovers, and integration into global value chains [Choranyi, Chorna, 2026]. Consequently, attracting foreign investment remains a strategic priority for governments seeking to enhance productivity, stimulate innovation, and strengthen international competitiveness [Fu, Liang, 2025]. While traditional FDI theories have emphasized factors such as market size, macroeconomic stability, trade openness, and resource availability as key determinants of investment decisions, the

ongoing digital transformation has broadened the range of factors influencing multinational enterprises' location choices [Mohanty et al., 2024].

In the contemporary digital economy, traditional location advantages alone are no longer sufficient to explain FDI flows [Bobenič Hintošová, Bódy, 2023]. Instead, digital infrastructure, innovation capabilities, and technological sophistication have become increasingly important determinants of investment attractiveness, particularly for knowledge-intensive and technology-oriented investments [Wang et al., 2025]. Within this context, the concept of Artificial Intelligence enabling factors has gained growing attention as an indicator of a country's readiness to support innovation, digital transformation, and advanced technological activities [Ali, Khan, 2025].

The effectiveness of AI adoption depends not only on the implementation of intelligent technologies but also on the existence of a supportive ecosystem that facilitates innovation and technological development [Prasetyo et al., 2025]. Such an ecosystem is characterized by advanced information and communication technology (ICT) infrastructure, sustained investment in research and development (R&D), and the capacity to generate and commercialize knowledge through innovation activities [Koutroumpis et al., 2020]. These factors collectively reflect a country's technological readiness and may provide positive signals to foreign investors regarding the quality of the business environment and its potential for knowledge-based economic activities [Radivojević et al., 2018].

Estonia represents one of the most remarkable international examples of successful digital transformation [Barde, 2024]. Despite its small population and limited natural resources, Estonia has developed a highly advanced digital ecosystem that has positioned the country among the world's leading digital economies [EC, 2025]. Through continuous investments in digital infrastructure, innovation policies, and technology-driven governance, Estonia has established a competitive environment that supports entrepreneurship, technological development, and international business activities. These achievements make Estonia an appropriate case study for examining the relationship between AI enabling factors and foreign direct investment attraction [Azzopardi et al., 2020].

Although a growing body of literature has investigated the relationship between technology and FDI, important gaps remain [Chen et al., 2022]. First, many studies have focused on individual technological indicators without considering them as components of a broader digital innovation ecosystem [Li et al., 2024]. Second, most empirical analyses rely on cross-country or panel data approaches, which may overlook the specific institutional and technological characteristics of highly digitalized economies [Mastac et al., 2026]. Third, limited attention has been devoted to examining the dynamic relationship between AI enabling factors and FDI at the country level, particularly regarding the distinction between short-run and long-run effects

[Özocaklı, 2026]. These limitations highlight the need for a focused empirical investigation capable of capturing the technological specificities and temporal dynamics of investment attraction.

Against this background, the present study investigates the impact of Artificial Intelligence enabling factors on Foreign Direct Investment attraction in Estonia during the period 2005–2024. Specifically, AI enabling factors are represented by Information and Communication Technology (ICT) development, Research and Development (R&D) expenditure, and patent applications (PAT), while Gross Domestic Product (GDP) is included as a control variable to account for the influence of market size on investment inflows.

To achieve this objective, the study employs the Autoregressive Distributed Lag (ARDL) approach using annual data obtained from the World Bank's World Development Indicators (WDI) database. The ARDL methodology is particularly suitable because it enables the estimation of both short-run dynamics and long-run equilibrium relationships among variables while accommodating relatively small sample sizes and different orders of integration.

This study contributes to the existing literature in several ways. First, it extends the analysis of FDI determinants by integrating digital infrastructure, research efforts, and innovation outputs within a unified AI-enabling framework. Second, it provides new econometric evidence from Estonia, one of the world's leading digital economies, which has received limited attention in country-specific time-series studies. Third, by distinguishing between short-run and long-run effects, the study offers a deeper understanding of how technological development influences investment attractiveness over time. Finally, the findings provide valuable insights for policymakers seeking to strengthen digital competitiveness and attract innovation-driven foreign investment in an increasingly technology-oriented global economy.

The remainder of the paper is organized as follows. Section 2 reviews the theoretical foundations and empirical literature related to AI enabling factors and FDI determinants. Section 3 presents the data, variables, and econometric methodology employed in the analysis. Section 4 reports and discusses the empirical findings. Finally, Section 5 concludes with the main findings, policy implications, and recommendations for future research.

Literature Review and Theoretical Framework

This section reviews the theoretical and empirical literature on the relationship between Artificial Intelligence enabling factors and Foreign Direct Investment attraction. It highlights the evolution of technological location advantages in the digital economy

and examines how ICT infrastructure, R&D capacity, and innovation output influence investment decisions. Based on previous studies and theoretical perspectives, the section develops the conceptual framework and hypotheses of the study.

Theoretical Foundations: Technological Location Advantages in the Digital Economy

Foreign Direct Investment (FDI) represents one of the most important mechanisms through which economies participate in global production networks, access advanced technologies, and enhance their long-term competitiveness [Onuogu et al., 2026]. The determinants influencing multinational enterprises' (MNEs) decisions regarding investment locations have been extensively studied within international economics and international business literature [Li, Du, 2025]. Traditionally, FDI theories emphasized economic factors such as market size, labor costs, natural resources, trade openness, and macroeconomic stability as the primary determinants of investment attractiveness [Chakrabarti, 2001]. However, the transformation toward a knowledge-based economy has fundamentally changed the nature of location advantages by increasing the importance of technological capabilities, innovation ecosystems, and digital readiness.

a. Dunning's Eclectic Paradigm and the Evolution of Location Advantages

The theoretical foundation of this study is based on Dunning's Eclectic Paradigm, also known as the OLI framework, which provides a comprehensive explanation of multinational enterprises' international investment decisions [Dunning, 1988; Dunning, Lundan, 2008]. According to this framework, firms undertake foreign investment when three complementary advantages are simultaneously available: ownership advantages, location advantages, and internalization advantages.

Ownership advantages refer to firm-specific assets that provide competitive advantages over local firms, including technological knowledge, managerial expertise, organizational capabilities, and intellectual property [Adarkwah, Malonæs, 2022]. Internalization advantages explain the benefits of controlling foreign activities rather than relying on external market transactions [Knight, Liesch, 2002]. Location advantages, however, represent the characteristics of host economies that determine their attractiveness as investment destinations [Fawaz, 2025].

Historically, location advantages were mainly associated with traditional economic characteristics, including natural resource availability, low production costs, market potential, and institutional stability [Sun et al., 2002]. These factors supported classical FDI motivations, including resource-seeking, market-seeking, and efficiency-seeking investment strategies [Moon, Yim, 2014].

Nevertheless, globalization, technological progress, and the expansion of knowledge-intensive industries have transformed the determinants of international investment [Petkovski et al., 2024]. Multinational enterprises increasingly seek locations that provide access not only to markets and production factors but also to knowledge resources, innovation capabilities, advanced infrastructure, and technological networks [Ladeira, Ferreira, 2026]. Consequently, technological capabilities have become a central component of modern location advantages.

In this context, countries' competitiveness in attracting FDI increasingly depends on their ability to develop technological environments that support innovation, digital transformation, and knowledge creation [Nguyen, 2025]. Economies with stronger technological capabilities are more likely to attract high-value foreign investment, particularly in sectors characterized by intensive use of knowledge and advanced technologies.

b. Digital Transformation and Artificial Intelligence as a New Dimension of Location Advantage

The digital transformation of economic activities has expanded the traditional framework of Foreign Direct Investment (FDI) determinants [Limnyuy, Mignamissi, 2026]. While classical theories emphasized factors such as market size, labor costs, natural resources, and macroeconomic stability, digitalization has introduced new technological dimensions influencing multinational enterprises' location decisions [Yang, 2026]. Digital technologies have transformed production processes, information management, and participation in global value chains [Goi et al., 2023], making technological capabilities an increasingly important source of investment attractiveness.

Among these technologies, Artificial Intelligence (AI) has emerged as a key driver of productivity, innovation, and competitiveness. However, the benefits of AI depend not only on technological applications but also on the existence of a supportive innovation ecosystem capable of generating and commercializing knowledge.

The National Innovation Systems (NIS) approach explains AI readiness as the outcome of interactions among firms, universities, research institutions, and governments. Within this framework, AI-enabling factors consist of three complementary dimensions: digital infrastructure, research and development (R&D) capacity, and innovation output. Together, these elements create an advanced technological environment that enhances a country's attractiveness to foreign investors by reducing operational costs, fostering innovation, and strengthening competitiveness. Consequently, economies with stronger AI-supportive ecosystems are better positioned to attract FDI.

This perspective aligns with broader scholarly evidence suggesting that Artificial Intelligence should not be viewed merely as a technological tool but rather as an evolu-

tionary force capable of reshaping entrepreneurial ecosystems, accelerating innovation processes, and enhancing national competitiveness [Bouguerra et al., 2026]. From this standpoint, AI-enabling capabilities extend beyond digital infrastructure to encompass institutional adaptability, knowledge creation, and innovation-driven governance, thereby reinforcing a country's technological location advantages.

Nevertheless, the economic implications of digitalization remain subject to ongoing academic debate. While many studies report positive effects of digital technologies on competitiveness and investment attractiveness, recent empirical evidence indicates that digitalization alone does not automatically translate into superior economic performance. For example, a panel study covering 17 advanced industrialized economies during the period 2010–2023 found that Internet Users (IU) and the Digital Competitiveness Score (DCS) did not exert statistically significant effects on manufacturing labor productivity [Yalouli et al., 2026]. These findings suggest that digital infrastructure constitutes a necessary but insufficient condition for sustainable economic gains, emphasizing the complementary roles of research capacity, institutional quality, human capital, and innovation ecosystems.

This argument also extends the traditional investment-location perspective. Although classical FDI theories emphasize relatively static determinants such as market size, labor costs, and natural resource endowments, contemporary research increasingly highlights the importance of strategic adaptability – the capacity of countries to rapidly reconfigure institutions, policies, and technological resources in response to global economic and technological change. Proactive governance, economic diversification, digital innovation, and policy flexibility have emerged as critical sources of competitive advantage, particularly for small open economies competing to attract high-value foreign investment [Bouguerra, Yalouli, 2025].

Estonia provides a compelling illustration of this transition. Beyond developing advanced digital infrastructure, the country has integrated Artificial Intelligence into its national investment promotion strategy through Invest Estonia, where AI-powered tools support investor services, accelerate business procedures, and enhance investment facilitation. This experience demonstrates that AI is evolving from a supporting technology into a strategic instrument for strengthening national investment competitiveness within the digital economy.

Literature Review: AI Enabling Factors and FDI Attraction

Recent studies indicate a shift in FDI research from traditional economic determinants toward technology-based explanations. Digital infrastructure, R&D capacity, and innovation performance have become increasingly important factors shaping investment attractiveness.

a. Digital Infrastructure and Foreign Direct Investment Attraction

Digital infrastructure plays a central role in economic competitiveness by improving connectivity, information exchange, and business efficiency [Hao et al., 2026]. According to transaction cost theory [Williamson, 1975], ICT development reduces information asymmetries and operational costs, thereby enhancing the attractiveness of host economies for multinational enterprises.

Empirical studies generally report a positive relationship between ICT development and FDI inflows [Hellmanzik, Schmitz, 2017]. Nevertheless, evidence from developing regions suggests that the impact of digitalization depends on complementary factors such as institutional quality, human capital, and absorptive capacity. Digital infrastructure alone may not guarantee positive outcomes without supportive economic conditions.

In Estonia, investments in e-government services, digital identity systems, and integrated digital platforms have created an advanced digital environment that facilitates entrepreneurship, innovation, and international business activities, strengthening the country's attractiveness to foreign investors [Tampuu, Masso, 2019].

b. Research and Development Capacity and Foreign Direct Investment Attraction

R&D capacity is a major determinant of technological progress and competitiveness. In knowledge-based economies, multinational enterprises increasingly seek locations offering strong research capabilities and innovation networks.

The absorptive capacity theory [Cohen, Levinthal, 1990] suggests that countries with stronger research systems are better able to acquire and utilize external knowledge, making them more attractive to foreign firms. Similarly, Dunning and Narula [1995] argue that multinational enterprises invest abroad not only to exploit markets but also to access strategic assets such as scientific knowledge and technological expertise [Dunning, Narula, 1995].

Empirical evidence generally supports the positive effect of R&D on FDI attraction [Belderbos et al., 2015; Kumar, 2001]. This relationship is particularly relevant in the context of AI, where continuous research, technological experimentation, and specialized skills are essential. Estonia's emphasis on innovation policies and technological education has contributed to the development of a knowledge-based economy capable of attracting technology-intensive investment [Belderbos et al., 2015; Kumar, 2001].

c. Innovation Output and Foreign Direct Investment Attraction

Innovation output reflects a country's ability to convert knowledge and research efforts into commercially valuable outcomes. Patent applications are widely used as indicators of technological capability and innovation performance [Griliches, 1990].

From the perspective of multinational enterprises, innovation performance signals the technological maturity of host economies. Countries with stronger patent activity provide favorable environments for knowledge-seeking investment strategies aimed at accessing technological resources and innovation networks [Jemberu, Metzker, 2026]. However, some research suggests that FDI does not always generate positive innovation outcomes and may even reduce domestic innovation through competitive pressures [Crescenzi, Gagliardi, 2018]. These mixed findings indicate that the impact of FDI depends on factors such as absorptive capacity, market structure, and institutional quality.

In Estonia, innovation output represents an important component of the country's digital development strategy and contributes to its reputation as a technology-oriented economy [Kalvet, 2012]. Consequently, innovation performance can be expected to enhance the country's ability to attract foreign investment.

Taken together, ICT infrastructure, R&D expenditure, and innovation output form an integrated AI-enabling ecosystem. While each factor contributes individually to investment attractiveness, their combined interaction creates stronger technological location advantages. Despite growing interest in these determinants, limited research has examined their joint influence on FDI [Al Balushi, Khalil, 2026]. This study addresses this gap by analyzing how these AI-enabling factors collectively affect FDI attraction in Estonia.

d. Towards an Integrated Ecosystem: The Synergy Among AI Enabling Factors

Beyond their individual contributions, it is the synergy among ICT infrastructure, R&D investment, and innovation output that constitutes a genuine AI-enabling ecosystem. Digital infrastructure (ICT) provides the foundational platform, but its potential is unlocked through sustained R&D expenditure, which creates new knowledge and technological capabilities [Liu et al., 2026], where the interactions between these factors are more important than their individual levels. For example, the effectiveness of ICT in fostering economic growth has been shown to be significantly moderated by FDI, suggesting that without the complementary inflow of foreign capital and knowledge, digital infrastructure alone may not reach its full potential [Noorbakhsh et al., 2001].

However, this integrative perspective remains largely underexplored in the empirical literature on FDI determinants. Most existing studies have examined digitalization, R&D intensity, and innovation output as separate and independent determinants, rath-

er than as interconnected components of a unified technological ecosystem. This fragmentation limits our understanding of how these factors collectively shape investment attractiveness, particularly in the context of AI-driven digital transformation. Consequently, there is a need for empirical investigations that explicitly model the interactive and synergistic effects of AI enabling factors on FDI attraction.

Estonia's Digital Innovation Ecosystem and Research Gap

Estonia provides a particularly relevant empirical context for examining the relationship between Artificial Intelligence enabling capabilities and Foreign Direct Investment attraction. Despite its small domestic market and limited natural resources, Estonia has developed one of the most advanced digital ecosystems internationally through a development strategy centered on digital transformation, technological innovation, and knowledge-based growth.

Since regaining independence in 1991, Estonia has considered digitalization as a strategic pathway for economic modernization. The country has invested significantly in information technologies, digital public services, and institutional frameworks supporting technological development. Initiatives such as electronic identification, online public services, and the X-Road data exchange platform have created an integrated digital environment that improves business efficiency and supports innovation activities.

This digital transformation has contributed to strengthening Estonia's attractiveness for international investors. A highly developed digital environment reduces operational barriers, facilitates entrepreneurship, and provides favorable conditions for companies operating in technology-intensive sectors. Estonia's experience demonstrates how technological capabilities can compensate for limitations related to market size and resource availability by creating alternative forms of location advantages.

Beyond digital infrastructure, Estonia has promoted innovation through policies supporting research activities, startup development, technological education, and collaboration between public institutions and private firms. The emergence of successful technology companies illustrates the country's capacity to transform digital capabilities into economic opportunities and international competitiveness.

Despite Estonia's recognition as a digital leader, empirical research examining the direct relationship between AI enabling factors and FDI attraction remains limited. Existing studies have largely focused on describing Estonia's digital transformation experience rather than quantitatively evaluating whether technological capabilities significantly influence foreign investment inflows over time.

Furthermore, several gaps remain in the broader empirical literature. First, most previous studies rely on cross-country panel approaches, which may not adequately capture the specific technological and institutional characteristics of individual economies.

This limitation is particularly relevant for small digitally advanced economies where technological capabilities represent a central component of competitiveness.

Second, previous studies generally examine digitalization, R&D capacity, and innovation performance as separate determinants of FDI rather than considering them as interconnected elements of an integrated AI enabling ecosystem. However, Artificial Intelligence development depends on the interaction between digital infrastructure, knowledge creation, and innovation capabilities.

Third, limited attention has been devoted to dynamic relationships between AI-related technological capabilities and FDI attraction. Since technological development and investment decisions evolve gradually over time, distinguishing between short-run effects and long-run equilibrium relationships is essential. Therefore, time-series econometric approaches such as the ARDL model provide an appropriate framework for analyzing this relationship.

This study addresses these gaps by examining Estonia as a specific case study and applying an ARDL approach to evaluate whether AI enabling factors contribute to attracting FDI during the period 2005–2024.

Hypothesis Development

Based on the theoretical foundations of the OLI paradigm, national innovation systems theory, and absorptive capacity theory, this study considers Artificial Intelligence enabling factors as a modern form of technological location advantage. In the digital economy, multinational enterprises increasingly evaluate host economies according to their capacity to provide advanced digital infrastructure, generate technological knowledge, and support innovation activities. Therefore, economies with stronger AI enabling capabilities are expected to create more attractive environments for foreign investors seeking knowledge-based opportunities and technological assets.

Accordingly, the theoretical hypothesis of this study is formulated as follows:

HT: The development of Artificial Intelligence enabling capabilities positively influences Foreign Direct Investment attraction in Estonia by strengthening technological location advantages and enhancing the national innovation ecosystem.

To empirically test this relationship using the ARDL approach, the following statistical hypothesis is proposed:

H1: Artificial Intelligence enabling factors, represented by ICT infrastructure, R&D capacity, and innovation output, have a positive and statistically significant impact on Foreign Direct Investment attraction in Estonia during the period 2005–2024.

This hypothesis will be examined by analyzing both short-run dynamics and long-run equilibrium relationships between AI enabling factors and FDI attraction. The null hypothesis assumes that AI enabling capabilities have no statistically significant effect

on FDI inflows, whereas the alternative hypothesis states that technological capabilities related to Artificial Intelligence contribute significantly to increasing Estonia's attractiveness as a destination for foreign investment.

Method and Result

Research Design and Econometric Approach

This study adopts a quantitative econometric approach to examine the relationship between Artificial Intelligence enabling factors and Foreign Direct Investment (FDI) attraction in Estonia during the period 2005–2024. The empirical analysis is designed to investigate whether improvements in the digital innovation ecosystem contribute to enhancing Estonia's ability to attract foreign investment.

Given the objective of identifying both short-run dynamics and long-run relationships among the variables, the study employs the Autoregressive Distributed Lag (ARDL) approach developed by [Pesaran et al., 2001]. The ARDL methodology is particularly suitable for this study because it allows the estimation of relationships between variables with different orders of integration, provided that none of the variables is integrated at the second difference level ($I(2)$). Furthermore, the approach is appropriate for relatively small sample sizes, which corresponds to the annual time-series dataset covering 2005–2024.

The empirical framework considers Foreign Direct Investment attraction as the dependent variable, while Artificial Intelligence enabling factors are represented through digital infrastructure, research and development capacity, and innovation output. Economic growth is introduced as a control variable to account for macroeconomic conditions affecting investment decisions.

Data Sources and Variables Description

This study examines the impact of artificial intelligence (AI) – related factors on foreign direct investment (FDI) flows in Estonia during the period 2005–2024. Estonia was selected as a case study due to its advanced digital economy, strong innovation environment, and leadership in e-governance and AI adoption.

Annual data were collected from the World Bank's World Development Indicators. The dependent variable is net FDI flows (as a percentage of GDP), while the independent variables cover key dimensions of Estonia's AI readiness and innovation capacity.

The study employs annual data for Estonia covering the period 2005–2024. The selected variables aim to capture the multidimensional foundations of artificial intelli-

gence (AI) development, including digital infrastructure, research intensity, and innovation capacity. Data were collected from the World Bank's World Development Indicators and complemented, where necessary, by other internationally recognized databases.

Table 1. Description of Variables

Variable	Symbol	Measurement	Source
Foreign Direct Investment	FDI	Net inflows (% of GDP)	World Bank https://data.worldbank.org/indicator/BX.KLT.DINV.WD.GD.ZS
Economic Growth	GDP	GDP (constant 2015 US \$)	World Bank https://data.worldbank.org/indicator/NY.GDP.MKTP.KD
Artificial Intelligence Infrastructure	ICT	Individuals Using the Internet (% of population)	World Bank https://data.worldbank.org/indicator/IT.NET.USER.ZS
Research and Development	R	R&D expenditure (% of GDP)	World Bank https://data.worldbank.org/indicator/GB.XPD.RSDV.GD.ZS
Innovation Output	PAT	Patent Applications by Residents	World Bank https://data.worldbank.org/indicator/IP.PAT.RESD

Source: [WB, 2026].

The original dataset consists of annual observations covering the period 2005–2024. To increase the number of observations required for ARDL estimation, the annual series were converted into monthly observations using quadratic interpolation in EViews 12. Consequently, all econometric procedures, including unit root tests, lag selection, cointegration analysis, and ARDL estimation, were performed using the interpolated monthly dataset.

However, it is important to note that the resulting monthly data are synthetic and should be interpreted as approximations rather than actual observations. To ensure the robustness of our findings, we conducted a sensitivity analysis by comparing the ARDL results obtained from both the original annual data and the interpolated monthly data. The consistency of the main findings across both datasets provides confidence in the reported results.

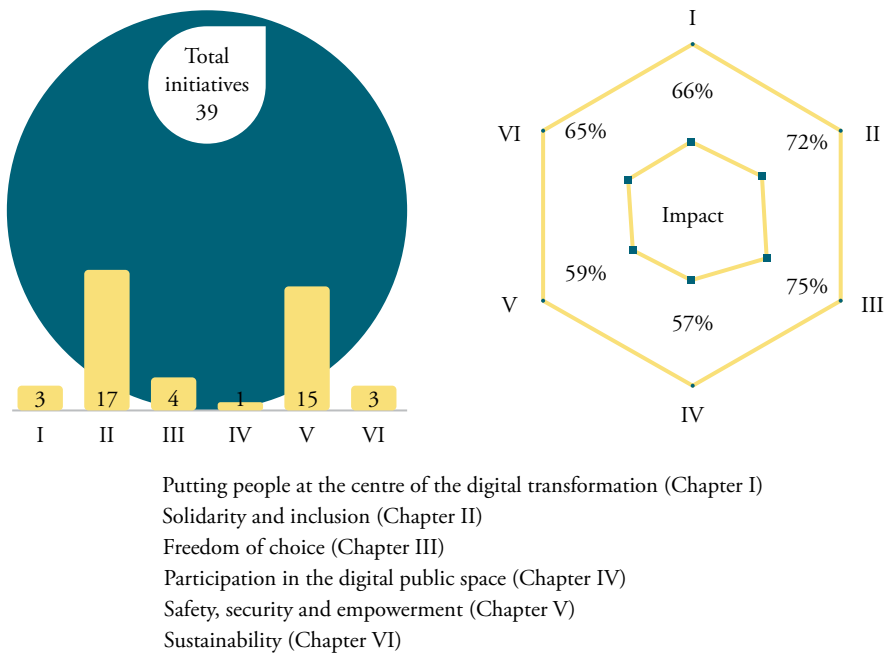
Given the absence of consistent and internationally comparable long-term data on AI adoption, investment, and deployment at the national level, this study follows the AI readiness and digital innovation literature by employing proxy indicators that reflect the technological and institutional conditions enabling AI development. In this context, ICT infrastructure, research and development (R&D) expenditure, and patent activity are considered essential components of AI readiness, as they represent digital capacity, knowledge creation, and innovation performance. These indicators allow the

study to examine how technological preparedness contributes to a country's attractiveness for foreign direct investment (FDI).

The selected variables represent three complementary dimensions of AI-enabling capabilities. Internet penetration captures the level of digital infrastructure and connectivity, R&D expenditure reflects the country's commitment to technological knowledge creation, while patent applications measure innovation outputs and the ability to transform knowledge into technological solutions.

To provide a broader understanding of Estonia's digital transformation environment, Figure (1) illustrates the distribution of national digital initiatives across six key dimensions and highlights their respective levels of impact.

Figure 1. Digital Rights and Principles



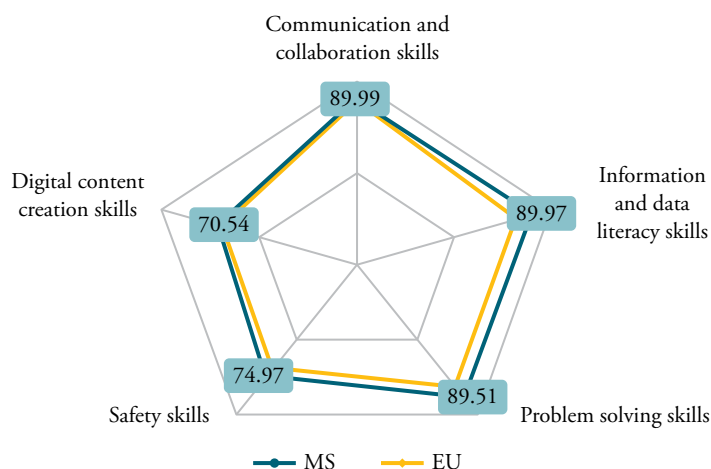
Source: [EC, 2025].

The figure illustrates the distribution of 39 digital initiatives across six dimensions of digital transformation in Estonia, highlighting differences in both the number of initiatives and their impact. The largest number of initiatives was recorded in Digital Solidarity and Inclusion (17 initiatives) and Digital Safety, Security, and Empowerment (15 initiatives), while six additional initiatives were launched in 2024, reflecting Estonia's continued commitment to the European Digital Decade objectives.

Regarding impact, Freedom of Choice achieved the highest score (75%), followed by Solidarity and Inclusion (72%), indicating effective policy implementation in these areas. In contrast, Participation in the Digital Public Space recorded the lowest impact level (57%), suggesting the need to strengthen citizen engagement in digital governance. The relatively limited activity in Fair Digital Environment also indicates the need for further policy efforts to ensure balanced digital development.

Overall, Estonia's experience shows that successful digital transformation depends not only on the number of initiatives but also on their effectiveness, strategic orientation, and capacity to generate tangible outcomes. Since human capital is a key driver of AI adoption, Figure (2) presents the distribution of digital skills in Estonia by age group and geography compared with the EU average.

Figure 2. The digital scene in Estonia



Source: [EC, 2025].

Estonia demonstrates a high level of basic digital skills, with 62.61% of the population possessing such skills in 2023, exceeding the EU average of 55.56%, and aiming to reach 80% by 2030. The country shows minimal gender disparity (1.07%) and limited educational and geographic gaps, with rural residents (56.99%) outperforming the EU rural average (47.50%). Young people aged 16–24 achieve the highest level of digital skills (86.84%), while the 65–74 age group records the lowest (22.67%). Estonia also surpasses the EU average across all Digital Skills Index dimensions, particularly in communication and collaboration (89.99%), whereas digital content creation remains the weakest area (70.54%).

These results highlight Estonia's successful model of digital inclusion and effective policies in reducing traditional digital divides. However, the significant generational gap between younger and older groups remains a major challenge, requiring targeted training for elderly citizens. Moreover, improving digital content creation skills is essential to move from digital consumption toward innovation and value creation. Overall, Estonia possesses a strong digital foundation, but future efforts should focus on transforming digital capabilities into broader economic and social benefits.

Econometric Analysis and Empirical Results

Before estimating the ARDL model, it is essential to examine the stationarity properties of the time series variables to avoid spurious regression results. Stationarity implies that the mean, variance, and autocorrelation structure of a time series do not change over time. To test for the presence of a unit root, this study employs two complementary tests: the Augmented Dickey-Fuller (ADF) test developed by Dickey and Fuller and the Phillips-Perron (PP) test proposed by Phillips and Perron.

a. Time Series Stationarity Analysis

To study the stationarity of the time series variables, two tests were used: the Dickey-Fuller Extended Test (ADF) and the Philipp Perron Test (PP), based on annual data. The results were as follows:

Table 2. Results of both the ADF and PP unit root tests

Unit root test table (PP)						
At Level		R	PAT	ICT	GDP	FDI
t-Statistic	With Constant	-1.5915	-1.8926	-6.7339	-1.6254	-1.5612
Prob.		0.4789	0.3326	0.0000	0.4622	0.4945
		n0	n0	***	n0	n0
t-Statistic	With Constant & Trend	-1.9028	-1.8118	-1.0650	-2.1752	-1.1373
Prob.		0.6373	0.6816	0.9246	0.4923	0.9119
		n0	n0	n0	n0	n0
t-Statistic	Without Constant & Trend	0.5378	-0.6979	2.2150	1.7024	-1.3584
Prob.		0.8286	0.4087	0.9929	0.9771	0.1595
		n0	n0	n0	n0	n0

At First Difference						
		d(R)	d(PAT)	d(ICT)	d(GDP)	d(FDI)
t-Statistic	With Constant	-3.4064	-3.1534	-3.1474	-3.4672	-3.4569
Prob.		0.0158	0.0302	0.0296	0.0133	0.0136
		**	**	**	**	**
t-Statistic	With Constant & Trend	-3.3618	-3.0800	-4.7695	-3.3712	-3.5572
Prob.		0.0693	0.1242	0.0018	0.0674	0.0445
		*	n0	***	*	**
t-Statistic	Without Constant & Trend	-3.3558	-3.1985	-2.1344	-3.1799	-3.6122
Prob.		0.0012	0.0021	0.0328	0.0021	0.0006
		***	***	**	***	***
Unit root test table (ADF)						
At Level		R	PAT	ICT	GDP	FDI
t-Statistic	With Constant	-1.9347	-2.7806	-3.8088	-1.6136	-0.9659
Prob.		0.3140	0.0697	0.0056	0.4678	0.7578
		n0	*	***	n0	n0
t-Statistic	With Constant & Trend	-2.6582	-2.7259	-2.8268	-3.5240	-1.2179
Prob.		0.2580	0.2320	0.1960	0.0480	0.8951
		n0	n0	n0	**	n0
t-Statistic	Without Constant & Trend	0.5479	-0.6690	-0.4792	1.4759	-1.0549
Prob.		0.8307	0.4211	0.5024	0.9635	0.2590
		n0	n0	n0	n0	n0
At First Difference						
		d(R)	d(PAT)	d(ICT)	d(GDP)	d(FDI)
t-Statistic	With Constant	-4.4313	-4.4346	-1.4231	-4.3421	-8.4645
Prob.		0.0009	0.0010	0.5620	0.0011	0.0000
		***	***	n0	***	***
t-Statistic	With Constant & Trend	-4.3957	-4.4494	-6.4123	-4.4082	-8.5922
Prob.		0.0056	0.0052	0.0000	0.0052	0.0000
		***	***	***	***	***
t-Statistic	Without Constant & Trend	-4.2958	-4.4865	-2.0129	-3.8435	-8.5072
Prob.		0.0001	0.0000	0.0434	0.0003	0.0000
		***	***	**	***	***

Notes: (*) Significant at the 10%; (**) Significant at the 5%; (***) Significant at the 1%. and (no) Not Significant *Mac-Kinnon (1996) one-sided p-values.

Source: Prepared by the researcher based on the outputs of the eViews 12 program.

The results of the unit root tests conducted using both the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests indicate that most of the time series variables are non-stationary at level form. The probability values (Prob.) do not allow the rejection of the null hypothesis of the presence of a unit root, suggesting that the variables FDI, GDP, PAT, and R suffer from non-stationarity at level. In contrast, the ICT variable shows evidence of stationarity at level under certain specifications, as its probability value is lower than the 5% significance level, indicating that it is integrated of order zero, $I(0)$.

After taking the first difference, the results of both the ADF and PP tests confirm that all variables become stationary at conventional significance levels, leading to the rejection of the unit root hypothesis. Therefore, the variables included in the model are integrated at mixed orders, $I(0)$ and $I(1)$, with no variable integrated of order two, $I(2)$.

Based on these findings, the integration properties of the variables justify the application of the cointegration methodology within the Autoregressive Distributed Lag (ARDL) bounds testing framework. This approach is appropriate for models combining variables that are stationary at level and variables that become stationary after first differencing. Accordingly, the ARDL methodology allows for the estimation of both short-run dynamics and long-run equilibrium relationships among the variables under investigation.

b. Estimation of the ARDL Model

Model Specification

After examining the stationarity properties of the variables through the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests, the results indicate that the variables are integrated at mixed orders, $I(0)$ and $I(1)$, with no variable integrated of order two, $I(2)$. Therefore, the Autoregressive Distributed Lag (ARDL) approach is considered appropriate for investigating the relationship among the variables under study.

Accordingly, this section presents the estimation of the cointegration model using the ARDL methodology to analyze the impact of artificial intelligence enabling factors on foreign direct investment attraction in Estonia during the period 2005–2024.

The functional relationship among the study variables can be expressed as follows:

$$FDI_t = f(GDP_t) + (ICT)_t + (PAT)_t + (R)_t$$

Where:

FDI_t : Foreign Direct Investment inflows (% of GDP), representing the dependent variable

GDP_t : Gross Domestic Product, reflecting market size and overall economic activity

ICT_t: Information and Communication Technology infrastructure, representing the digital foundations that facilitate the adoption and development of artificial intelligence technologies

PAT_t: Patent Applications, used as a proxy for innovation output and technological capability

R_t: Research and Development (R&D) expenditure, reflecting a country's investment in knowledge creation and technological advancement

Based on this specification, the ARDL model is estimated to examine both the long-run equilibrium relationship and the short-run dynamics between foreign direct investment and the selected artificial intelligence enabling factors.

Estimation of the Unrestricted Error Correction Model and Selection of Optimal Lag Lengths

Before estimating the ARDL model, it is necessary to determine the optimal lag structure for the dependent and explanatory variables. The selection of appropriate lag lengths is crucial for capturing the dynamic relationships among variables and ensuring the robustness of the estimated results.

To this end, several lag combinations were evaluated using the automatic lag selection procedure available in EViews 12. The optimal model was selected based on the Akaike Information Criterion (AIC), which aims to identify the specification that minimizes information loss while maintaining model parsimony.

The unrestricted Error Correction Model (ARDL-ECM) was estimated using the Ordinary Least Squares (OLS) method, and the results of the lag selection procedure are presented in Table 3.

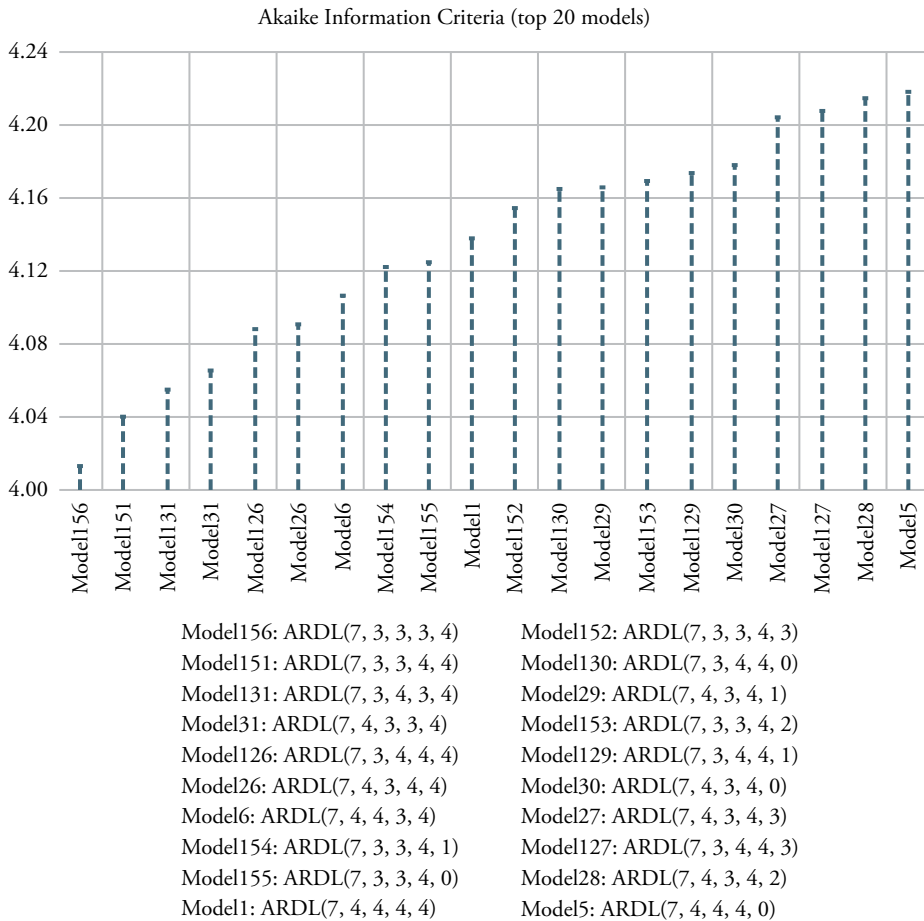
Table 3. Optimal Lag Length Selection for the Estimated ARDL Model

Model	Maximum Lag Lengths Considered	Optimal Lag Structure (AIC)
ARDL Model	(7,4,4,4,4)	ARDL (7,3,3,3,4)

Source: Author's calculations based on EViews 12 outputs.

The results reported in Table 3 indicate that the optimal specification selected according to the Akaike Information Criterion (AIC) is ARDL(7,3,3,3,4). This specification was subsequently adopted for the estimation of the long-run relationship and short-run dynamics between foreign direct investment and the selected artificial intelligence enabling factors in Estonia.

As shown below:

Figure 3. Testing of optimal lag periods for selected and estimated models

Source: Based on the output of EViews 12.

Figure 03 presents the Akaike Information Criterion (AIC) values for the top 20 estimated ARDL models. The results indicate that the ARDL(7,3,3,3,4) specification yields the lowest AIC value among all competing models, suggesting that it is the optimal model. Therefore, this specification was selected for the subsequent cointegration analysis and the estimation of both long-run and short-run relationships among the study variables.

Since the ARDL model was estimated using the interpolated monthly dataset, the selected lag structure ARDL(7,3,3,3,4) reflects monthly adjustment dynamics rather than annual lags. The lag order was selected automatically using the Akaike Information Criterion (AIC), which identified the specification that provides the best statisti-

cal fit among the estimated models. Accordingly, the selected lag structure should be interpreted as representing short-run monthly dynamics derived from the temporally disaggregated data, while the original annual observations remained the primary source of the analysis.

ARDL Bounds Test for Cointegration

To examine the existence of a long-run equilibrium relationship among the study variables, the ARDL Bounds Testing approach developed by [Pesaran et al., 2001] was employed. The test is based on comparing the calculated F-statistic with the critical value bounds.

The null hypothesis states that there is no long-run relationship among the variables, while the alternative hypothesis assumes the existence of a long-run cointegrating relationship.

As reported in Table 4, the calculated F-statistic (6.4818) exceeds the upper critical bound value at the 5% significance level (3.49), as well as at the 1%, 2.5%, and 10% significance levels. Therefore, the null hypothesis of no long-run relationship is rejected in favor of the alternative hypothesis. This result confirms the existence of a long-run equilibrium relationship between foreign direct investment and the selected artificial intelligence enabling factors in Estonia. Consequently, the estimation of the long-run ARDL coefficients and the Error Correction Model (ECM) is justified.

Table 4. Results of the ARDL Bounds Test

Model	k	F-statistic	Upper Bound (5%)	Decision
ARDL Model	4	6.4818	3.49	Cointegration exists

Source: Author's calculations based on EViews 12 outputs.

c. ARDL model estimation results and error correction analysis

After confirming the existence of a long-term equilibrium relationship between the variables included in the model through bounds testing, this section presents the results of the distributed interval autoregression (ARDL) model estimation. Table (4) shows the results of the error correction model (ECM) estimated within the ARDL framework. The top of the table shows the short-run coefficients, which represent the immediate and delayed effects of changes in the explanatory variables on foreign direct investment flows, while the bottom shows the long-run coefficients, which reflect the equilibrium relationship between the variables over time.

Table 5. Error correction model estimation according to the ARDL methodology for the model

Conditional Error Correction Regression				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-21.06554	8.913257	-2.363394	0.0358
FDI(-1)*	-0.869162	0.349004	-2.490407	0.0284
GDP(-1)	2.85E-09	1.02E-09	2.794220	0.0162
ICT(-1)	-0.672313	0.291783	-2.304151	0.0399
PAT(-1)	0.023828	0.081830	0.291192	0.7759
R(-1)	7.954369	3.608034	2.204627	0.0477
D(FDI(-1))	1.192636	0.324190	3.678821	0.0032
D(FDI(-2))	-1.143653	0.353448	-3.235701	0.0071
D(FDI(-3))	1.138614	0.351153	3.242504	0.0071
D(FDI(-4))	-1.582868	0.421644	-3.754035	0.0028
D(FDI(-5))	0.404757	0.202707	1.996758	0.0690
D(FDI(-6))	-0.814240	0.235892	-3.451745	0.0048
D(GDP)	5.90E-09	1.48E-09	3.984277	0.0018
D(GDP(-1))	-1.85E-09	8.17E-10	-2.258459	0.0433
D(GDP(-2))	-1.88E-09	8.62E-10	-2.182246	0.0497
D(ICT)	-0.289172	0.643211	-0.449576	0.6610
D(ICT(-1))	0.194102	0.425540	0.456131	0.6564
D(ICT(-2))	1.822913	0.602283	3.026670	0.0105
(PAT)	0.092538	0.098881	0.935853	0.3678
D(PAT(-1))	0.055072	0.081242	0.677880	0.5107
D(PAT(-2))	0.191379	0.083354	2.295985	0.0405
D(R)	1.657275	5.681562	0.291694	0.7755
D(R(-1))	0.303166	6.350945	0.047736	0.9627
D(R(-2))	4.265563	6.893304	0.618798	0.5476
D(R(-3))	9.753098	4.878061	1.999380	0.0687

* p-value incompatible with t-Bounds distribution.

Levels Equation				
Case 2: Restricted Constant and No Trend				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
GDP	3.28E-09	7.23E-10	4.530116	0.0007
ICT	-0.773519	0.164489	-4.702562	0.0005
PAT	0.027415	0.085829	0.319418	0.7549
R	9.151773	2.476579	3.695328	0.0031
C	-24.23662	10.66802	-2.271894	0.0423
EC = FDI - (0.0000*GDP - 0.7735*ICT + 0.0274*PAT + 9.1518*R - 24.2366)				

Source: Author's calculations based on EViews 12 outputs.

It can be observed from the table above that the error correction coefficient (γ) has a negative value of (-0.8691) and is statistically significant at the 5% level, with a probability value of (0.0284) , which is lower than (0.05) . The negative and significant sign of the error correction term confirms the existence of a long-run equilibrium relationship among the variables included in the model and indicates that short-run deviations are corrected over time toward the long-run equilibrium path.

Furthermore, the value of the error correction coefficient (-0.8691) indicates that approximately 86.9% of short-run disequilibria resulting from temporary shocks are corrected within one period. Since the data used in this study are monthly, this implies that the adjustment process occurs within one month, reflecting a relatively high speed of convergence toward the long-run equilibrium relationship.

Estimated model:

$$FDI_t = -24.2366 + 0.0000 * GDP_t + 0.0077 * ICT_t + 0.0002 * PAT_t - 0.0915 * R + \varepsilon_t$$

Long-run Relationship Analysis

The results of the long-run equation (Levels Equation) reveal different effects of the explanatory variables on foreign direct investment. First, economic growth (GDP) exhibits a positive and statistically significant effect on FDI, with a coefficient of $(3.28E-09)$ and a probability value of (0.0007) . This result indicates that improvements in economic performance and increases in market size contribute to enhancing the attractiveness of the economy for foreign investors. A larger and more dynamic economy provides multinational enterprises with greater opportunities for production, market expansion, and investment profitability.

Regarding digital infrastructure (ICT), the results show a negative and statistically significant relationship with FDI in the long run, with a coefficient of (-0.7735) and a probability value of (0.0005) . This finding suggests that, despite the importance of digital development, the expansion of ICT infrastructure alone was not sufficient to generate positive effects on FDI attraction during the study period. This result may be explained by the fact that digital infrastructure must be accompanied by complementary factors, such as digital skills, innovation capacity, institutional quality, and a favorable business environment, in order to translate technological progress into investment advantages.

Although the estimated coefficient of ICT is negative and statistically significant, this finding should not be interpreted as evidence that digital infrastructure discourages foreign direct investment. Instead, it reflects Estonia's advanced level of digital maturity,

where internet penetration and digital connectivity have already reached near-universal levels. Under such conditions, further improvements in basic ICT infrastructure are likely to yield diminishing marginal benefits in attracting foreign investment. Consequently, multinational enterprises may increasingly base their investment decisions on more advanced determinants, including research and development intensity, artificial intelligence capabilities, innovation capacity, cybersecurity readiness, and the availability of highly skilled human capital. Therefore, the negative ICT coefficient should be interpreted as a saturation effect associated with a highly digitalized economy rather than as an adverse impact of digital infrastructure on FDI.

Therefore, the negative ICT coefficient should be interpreted as a saturation effect associated with a highly digitalized economy rather than as an adverse impact of digital infrastructure on FDI [OECD, 2024].

In contrast, patent applications (PAT) do not appear to have a statistically significant impact on FDI in the long run. The estimated coefficient is (0.0274), with a probability value of (0.7549). This indicates that technological innovation measured through patent activity did not constitute a significant determinant of FDI inflows during the analyzed period. This may reflect the limited ability of patent outputs alone to capture the commercial exploitation of innovation and its attractiveness to multinational firms.

Furthermore, research and development expenditure (R) has a positive and statistically significant impact on FDI, with a coefficient of (9.1518) and a probability value of (0.0031). This result highlights the importance of technological capabilities and knowledge creation in attracting foreign investment. Countries with stronger research and development capacities are more likely to provide location advantages for multinational enterprises seeking innovation-driven investment opportunities.

Accordingly, the estimated long-run relationship can be expressed as follows:

$$FDI_t = -24.2366 + 0.00000000328GDP_t - 0.77351ICT_t + 0.274PAT_t - 9.1518R_t + \epsilon_t$$

Short-run Dynamics and Error Correction Mechanism

The results of the Error Correction Model indicate that the error correction coefficient associated with the lagged FDI variable, represented by FDI (-1), is negative and statistically significant. The coefficient value is estimated at (-0.8691), with a probability value of (0.0284), confirming the existence of a valid adjustment mechanism toward the long-run equilibrium relationship.

The negative and significant value of the error correction term confirms that deviations from the long-run equilibrium are corrected over time. Specifically, the coefficient indicates that approximately 86.9% of short-run disequilibria are corrected within

one period, reflecting a relatively rapid adjustment process of FDI inflows toward their long-run equilibrium path.

The short-run coefficients reveal that past values of FDI significantly influence current FDI inflows. Several lagged changes of FDI show statistically significant coefficients, indicating the presence of dynamic persistence in foreign investment flows, where previous investment decisions affect current investment patterns.

Economic growth (GDP) also demonstrates a positive and statistically significant short-run effect in the current period, with a coefficient of (5.90E-09) and a probability value of (0.0018). However, some lagged GDP changes exhibit negative effects, suggesting that the short-run response of FDI to economic growth may involve adjustment dynamics before reaching long-run equilibrium.

For ICT, the short-run results indicate that most coefficients are statistically insignificant, except for the second lag of ICT, which has a positive and significant effect. This suggests that the impact of digital infrastructure on FDI attraction may require a time lag before becoming fully effective.

Regarding patent applications (PAT), the short-run coefficients are generally insignificant, except for the second lag, which records a positive and statistically significant effect. This implies that innovation outputs may require time before being transformed into economic advantages capable of influencing foreign investors' location decisions.

Finally, research and development (R) does not show significant short-run effects, although its long-run coefficient remains positive and significant. This indicates that the benefits of R&D investment in attracting FDI are mainly realized through accumulated technological capabilities rather than immediate effects.

Overall, the ARDL estimation results confirm the existence of a stable long-run relationship among the variables included in the model. The significant and negative error correction coefficient demonstrates the validity of the adjustment mechanism and confirms that short-run deviations are rapidly corrected toward the long-run equilibrium path. These findings support the suitability of the ARDL approach for analyzing the determinants of FDI within the context of the digital economy.

d. Diagnostic Tests of the Estimated ARDL Model

Within the framework of estimation using the Ordinary Least Squares (OLS) method, the validity and reliability of the estimated ARDL model require that the residuals satisfy several basic assumptions, including normal distribution, absence of serial correlation, and homoscedasticity. Therefore, a set of diagnostic tests was conducted to verify the adequacy of the estimated model and ensure that it meets the required econometric assumptions. The main diagnostic tests include the normality test, the serial correlation test, and the heteroscedasticity test. The obtained results are presented as follows:

Normality Test of Residuals

The Jarque-Bera test results indicate that the probability value is (0.8035), which is higher than the 5% significance level. Therefore, the null hypothesis of normally distributed residuals cannot be rejected. This result confirms that the residuals of the estimated ARDL model follow a normal distribution, indicating the validity of the model specification from this perspective.

Table 6. Results of the Normality Test

Test	Jarque-Bera	Probability
Value	0.4375	0.8035

Source: Compiled by the author based on the outputs of EViews 12.

Serial Correlation Test

Table 7. Breusch-Godfrey Serial Correlation LM Test Results

Test	F-statistic	Probability
Breusch-Godfrey Serial Correlation LM Test	1.3978	0.2915

Source: Compiled by the author based on the outputs of EViews 12.

The Breusch-Godfrey Serial Correlation LM test shows that the F-statistic value is (1.3978), with a probability value of (0.2915), which is higher than the critical significance level of 5%. Therefore, the null hypothesis of no serial correlation in the residuals cannot be rejected. This indicates that the model does not suffer from an autocorrelation problem, and the estimated coefficients are not affected by serial dependence among error terms.

Heteroscedasticity Test

Table 8. ARCH Heteroscedasticity Test Results

Test	F-statistic	Probability
Heteroskedasticity Test: ARCH	0.02296	0.8804

Source: Compiled by the author based on the outputs of EViews 12.

The ARCH test results show that the F-statistic value is (0.02296), while the corresponding probability value is (0.8804), which exceeds the 5% significance level.

Consequently, the null hypothesis of homoscedastic residuals cannot be rejected. This confirms that the residual variance remains constant over time and that the estimated ARDL model does not suffer from a heteroscedasticity problem.

Overall, the diagnostic tests confirm the adequacy and reliability of the estimated ARDL model. The residuals are normally distributed, free from serial correlation, and characterized by constant variance. Therefore, the model satisfies the main econometric assumptions required for valid estimation and inference.

(See Appendix No. 3)

e. Structural Stability Test of Model Parameters

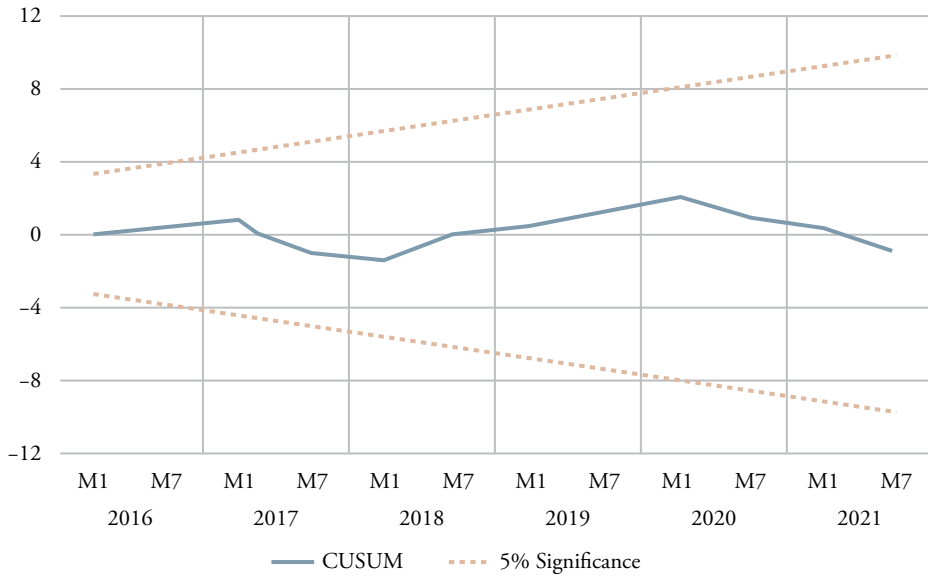
To verify that the data used in the study are free from structural changes and to assess the stability of the estimated coefficients, two structural stability tests proposed by Pesaran et al. were applied. These tests are widely used within the ARDL framework to examine the stability of model parameters in both the short-run and long-run relationships.

The first test is the Cumulative Sum of Recursive Residuals (CUSUM) test, while the second is the Cumulative Sum of Squares of Recursive Residuals (CUSUM of Squares) test. The ARDL model parameters are considered structurally stable if the plots of both tests remain within the critical bounds at the 5% significance level. In this case, the null hypothesis of parameter instability is rejected, and the alternative hypothesis of coefficient stability is accepted throughout the study period.

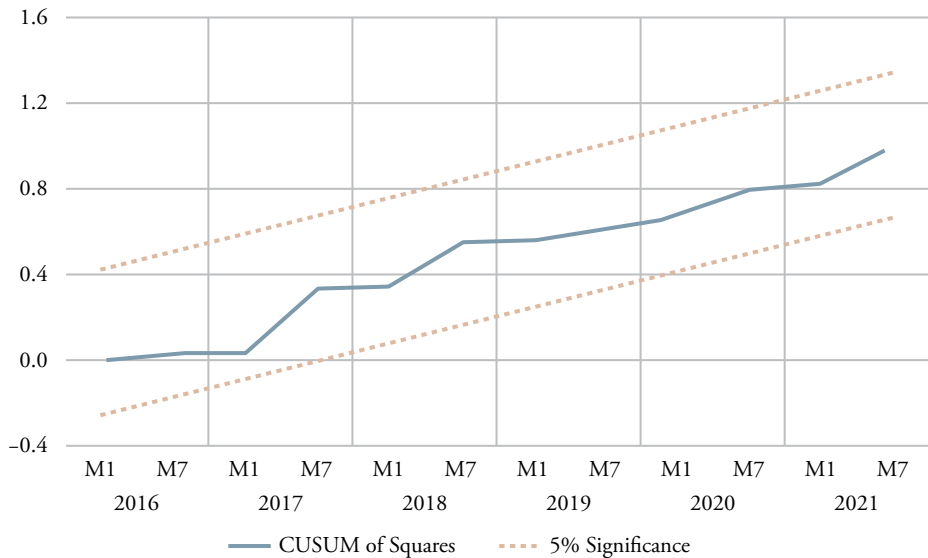
First: Stability tests of the foreign direct investment model

The graphical results presented above indicate that the CUSUM statistic remains within the critical boundaries at the 5% significance level. This confirms the structural stability of the estimated coefficients over the study period. Similarly, the CUSUM of Squares test remains inside the critical region, providing additional evidence that the model does not suffer from structural instability.

Therefore, it can be concluded that the estimated ARDL model is stable and consistent over time, and that there is a high degree of compatibility between the short-run dynamics and the long-run equilibrium relationship. This confirms the reliability of the estimated results and supports the validity of the model for explaining the determinants of FDI during the study period.

Figure 4. CUSUM Test for Model Stability

Source: Compiled by the author based on the outputs of EViews 12.

Figure 5. CUSUM of Squares Test for Model Stability

Source: Based on the output of EViews 12.

Discussion

The findings of this study provide important insights into the relationship between Artificial Intelligence (AI) enabling factors and Foreign Direct Investment (FDI) attraction in Estonia during the period 2005–2024. Overall, the ARDL results confirm the existence of a stable long-run equilibrium relationship between FDI and the selected technological variables, supporting the theoretical argument that technological capabilities constitute an increasingly important source of location advantages in the digital economy.

The positive and statistically significant effect of GDP on FDI inflows confirms the relevance of traditional FDI theories, particularly Dunning's Eclectic Paradigm, which emphasizes market size as a fundamental determinant of investment attractiveness. Although Estonia is a relatively small economy, sustained economic growth appears to signal favorable business opportunities and macroeconomic stability, thereby encouraging foreign investors. This result is consistent with previous empirical studies that identify economic growth as a major driver of FDI attraction.

A particularly interesting finding concerns the long-run negative effect of ICT development on FDI. While the theoretical literature generally predicts a positive relationship between digital infrastructure and investment attraction, the Estonian case suggests a more complex dynamic. One possible explanation is that digital infrastructure alone is insufficient to generate investment advantages when it reaches a relatively mature stage of development. In highly digitalized economies such as Estonia, foreign investors may place greater emphasis on complementary factors, including advanced skills, innovation ecosystems, research capacity, and institutional quality. Consequently, further expansion of ICT infrastructure may exhibit diminishing marginal returns with respect to FDI attraction. This finding supports the argument that digital readiness should be viewed as a multidimensional ecosystem rather than as a single technological indicator.

The results also demonstrate that research and development expenditure exerts a strong positive and statistically significant effect on FDI in the long run. This finding highlights the strategic importance of knowledge creation and technological capability accumulation in attracting foreign investment. Multinational enterprises increasingly seek locations that provide access to research networks, innovation activities, and highly skilled human capital. Therefore, Estonia's continuous investment in R&D appears to strengthen its technological location advantages and improve its attractiveness to knowledge-seeking and innovation-driven foreign investors. This result is consistent with absorptive capacity theory and previous studies emphasizing the role of R&D in enhancing investment competitiveness.

In contrast, patent applications do not exert a statistically significant influence on FDI inflows in the long run. Although patents are commonly used as indicators of

innovation output, they may not fully capture the commercial value of innovation or its direct relevance to foreign investors. In Estonia's case, foreign firms may be more interested in the broader innovation environment and research capabilities than in the volume of patent registrations alone. This result suggests that innovation outputs need to be effectively commercialized and integrated into productive activities before generating measurable effects on investment attraction.

The short-run results further reveal that the impact of technological variables is not immediate. While ICT and patent activity show some delayed positive effects, R&D expenditure does not produce significant short-term impacts. This finding indicates that the benefits of technological investments accumulate gradually and materialize over longer periods. Such evidence reinforces the importance of adopting a long-term perspective when evaluating the contribution of AI-related capabilities to investment attractiveness.

Overall, the findings support the view that foreign investors are increasingly attracted by comprehensive innovation ecosystems rather than by isolated technological indicators. Estonia's experience demonstrates that the interaction between economic performance, research capacity, digital transformation, and institutional support creates a favorable environment for attracting technology-intensive foreign investment. The results therefore contribute to the emerging literature on AI readiness and FDI by highlighting the importance of technological location advantages in the digital economy.

Conclusion

This study investigated the impact of Artificial Intelligence (AI) enabling factors on foreign direct investment (FDI) attraction in Estonia over the period 2005–2024 using the Autoregressive Distributed Lag (ARDL) approach. The analysis was motivated by the increasing importance of digital transformation, innovation ecosystems, and technological capabilities in shaping investment decisions within knowledge-based economies. By examining the long-run and short-run relationships between FDI and selected AI-related determinants, the study provides new empirical evidence from one of the world's most digitally advanced economies.

The empirical findings confirm the existence of a stable long-run equilibrium relationship between FDI and the selected explanatory variables. Economic growth (GDP) and research and development expenditure (R) exert positive and statistically significant effects on FDI, emphasizing the critical role of market performance and knowledge creation in strengthening a country's attractiveness to foreign investors. In contrast, the ICT variable exhibits a negative and statistically significant long-run coefficient. Rather than indicating that digital infrastructure discourages foreign investment, this result

reflects Estonia's advanced level of digital maturity, where widespread digital connectivity has already been achieved. Under such conditions, additional investments in basic ICT infrastructure may generate diminishing marginal benefits for attracting FDI, while investors increasingly value more sophisticated determinants such as research capacity, AI readiness, innovation capability, cybersecurity, and highly skilled human capital. Patent applications, although positively associated with FDI, were not statistically significant, suggesting that innovation outputs alone are insufficient to enhance investment attractiveness unless supported by an integrated innovation ecosystem.

The estimated error correction model indicates a relatively rapid adjustment toward long-run equilibrium, confirming the dynamic stability of the estimated relationships. Furthermore, the diagnostic and stability tests demonstrate that the estimated ARDL model satisfies the principal econometric assumptions, indicating that the empirical findings are statistically reliable and robust.

From a policy perspective, the results suggest that governments aiming to attract technology-intensive and innovation-driven foreign investment should move beyond policies focused solely on expanding digital infrastructure. Instead, greater emphasis should be placed on strengthening research and development activities, improving AI capabilities, enhancing digital governance, promoting knowledge commercialization, expanding innovation networks, and investing in advanced human capital. Estonia's experience demonstrates that sustainable FDI attraction increasingly depends on the quality of the national innovation ecosystem rather than on digital infrastructure alone.

This study contributes to the existing literature by extending the analysis of FDI determinants beyond conventional macroeconomic variables to include AI-enabling factors within the context of a highly digitalized economy. It also provides empirical evidence that the contribution of ICT infrastructure to FDI attraction becomes more nuanced as countries reach advanced stages of digital development. These findings enrich the growing literature on digital transformation, artificial intelligence, and international investment by highlighting the importance of innovation quality rather than digital infrastructure quantity.

Overall, the study concludes that artificial intelligence enabling capabilities constitute an increasingly important source of modern location advantages. In digitally mature economies, the ability to attract high-value foreign direct investment depends not only on digital infrastructure but also on the successful integration of research, innovation, artificial intelligence, and human capital into a coherent and competitive innovation ecosystem. Such an integrated strategy is likely to strengthen long-term economic competitiveness and enhance countries' capacity to attract sustainable, technology-intensive foreign investment in the evolving global digital economy.

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