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AI-Related Technological Capability and Economic Growth in Cyprus: Exploratory Macroeconomic Evidence

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Abstract

Artificial intelligence (AI) may influence economic performance through productivity, innovation, and the diffusion of advanced technologies, but direct country-level measures of AI adoption remain limited for small economies. This study examines the association between AI-related technological capability and economic growth in Cyprus. The descriptive analysis covers 1993–2024, while the econometric analysis uses the common annual sample for 2008–2024 after introducing one-period lags. High-technology exports as a percentage of manufactured exports are treated as an indirect indicator of technological sophistication and absorptive capacity, rather than as a direct measure of AI adoption. A sequential distributed lag ordinary least squares framework introduces current and lagged high-technology exports, merchandise trade, and inflation, with heteroskedasticity-consistent HC3 standard errors. A COVID-19 indicator for 2020–2021 and an observation-exclusion sensitivity analysis are used to assess the influence of exceptional pandemic-era movements. The preferred specification explains a substantial share of annual GDP growth variation, but the small sample requires cautious interpretation. The estimates indicate a positive contemporaneous and a negative lagged association for high-technology exports, a stronger lagged than contemporaneous trade association, and opposite-signed current and lagged inflation coefficients. The COVID-19 indicator is statistically insignificant and does not materially alter the principal coefficient pattern. Complementary DESI, Eurostat enterprise AI use, and ICT employment indicators show that Cyprus has broadly adequate digital inputs while enterprise AI adoption has not yet reached the European Union average, indicating considerable scope for further diffusion. The findings are exploratory statistical associations and do not identify causal effects of AI. The study contributes a country-specific macroeconomic assessment of technological capability, digital readiness, and growth in a small, highly open economy.



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Keywords: artificial intelligence; technological capability; high-technology exports; economic growth; Cyprus; digital transformation

1. Introduction

AI has become a key element of technological change due to its capabilities for learning, forecasting, recognizing patterns, automatization, and decision-making. The economic

significance of artificial intelligence is not limited to individual applications, as AI technologies can help in complementary skilled labor, the reorganization of production processes, information management, and product/service development. However, the macroeconomic measurement of AI is complicated, especially for small economies that do not have long annual series on firm-level adoption, AI investments, and sectoral productivity. In this respect, this paper makes a distinction between AI adoption and technological capability that may underpin the development and spread of AI technology. High-tech exports serve as an indirect measure of technological capability, innovative capacity, and absorptive capacity rather than as direct evidence of AI usage (Acemoglu et al., 2022; Frank et al., 2019; Gao & Feng, 2023; Parteka & Kordalska, 2023; Trabelsi, 2024).

The case of Cyprus offers itself for analysis. Cyprus is an open economy in Europe whose GDP is closely related to tourism, financial and professional services, shipping, trade, and an emerging ICT sector. Such structure gives an environment in which productivity improvements can be due to IT while, at the same time, making the country's annual growth vulnerable to external demand, international trade, prices, and shocks (Challoumis, 2024). The available European measures point to the fact that Cyprus has a level of readiness for the digital revolution and a skill set similar to the EU average; however, the adoption of AI technology by enterprises is less advanced.

The research poses answers to three interrelated questions. First, what has been the trajectory of the selected measures of technological capability and digital readiness in Cyprus? Second, is the GDP growth rate in the economy related to current and lagged exports of high-technology goods when controlling for trade openness and inflation? Third, are the regression results robust to the special drop and subsequent recovery during the COVID-19 recession? To answer these questions, descriptive statistics are presented for the period 1993–2024, alongside sequential distributed lag regressions covering the period 2008–2024.

Therefore, the contribution of the paper is methodologically and nationally specific. As opposed to measuring the causal effect of AI adoption on economic growth, the present study focuses on assessing the exploratory relationship between economic growth and a more comprehensive measure of AI-relevant technological capability. It turns out that the contemporary and lagged dimensions of technological capability, trade and inflation do not act universally, while the pandemic effect does not add much explanatory power after these factors are controlled for. These results are discussed along with evidence from DESI, Eurostat and ICT employment to draw the difference between digital inputs and firm adoption.

2. Literature Review

The literature related to this paper may be categorized into three interrelated themes. The first theme deals with AI, automation, technology and productivity; the second theme analyzes the organizational determinants of enterprise adoption; while the third theme focuses on the labor market, regulations and distributive effects. The key takeaway across all these themes is not the fact that AI generates an automatic growth dividend, but rather that its economic value is dependent on other factors such as capital, skills, information, organization, institutions and the reorganization of production (Lu & Zhou, 2021; Parteka & Kordalska, 2023; Trabelsi, 2024; Yuan et al., 2024).

Productivity research underscores both opportunities and diversity. AI has the capacity to increase output through the automation of certain activities, enhanced forecasting, innovation, and the supplementation of human expertise (Abid, 2025; Chivu, 2022; Dejanović, 2025; Geetha et al., 2024; Singh, 2025; Wang et al., 2024); however, it could take time to realize these benefits due to costs associated with its implementation and organizational

change. While empirical evidence at the firm level tends to show that the use of AI is associated with greater innovation and income-based performance in firms, especially in combination with cloud computing, the Internet of Things, big data analytics, and appropriate skill sets, these findings cannot be generalized to the macroeconomic level in Cyprus due to the non-representativeness of firms adopting AI and macro-factors (Ardito et al., 2024; Azizoglu, 2026; Cüneyt, 2025; Gans, 2023; Gao & Feng, 2023; Kopka & Fornahl, 2023; Mohamed et al., 2026; Olutimehin et al., 2026; Schwaeke et al., 2024; Socol et al., 2025).

Another line of research deals with the circumstances conducive to adoption or otherwise. From a Technology–Organization–Environment point of view, technological readiness, management support, firm size, financial means, employee capabilities, competitive pressure, and legal regulation play important roles. Small- and medium-sized firms often have to deal with disproportionately high costs, lack of access to expertise, uncertainty regarding payback, and integration problems when implementing AI technologies. This problem is especially pertinent for Cyprus, where the bulk of the enterprise population consists of small firms and service enterprises (Anh et al., 2024; Arroyabe et al., 2024; Badghish & Soomro, 2024; Cimino et al., 2025; Felemban et al., 2024; Kádárová et al., 2026; Kovič et al., 2024; Maghfirah & Eni, 2024; Nawaz, 2026; Pitić et al., 2026; Sánchez et al., 2025; Soomro et al., 2025; Yesuf & Fields, 2025; Zeb et al., 2025). Beyond firm performance, a growing strand of research relates AI adoption to sustainability transitions, green finance, and environmentally oriented investment and reporting (Bataleblu et al., 2024; Giner & Luque-Vílchez, 2022; Kumar et al., 2025; Li et al., 2025; Omri et al., 2025; Sadiq et al., 2025; Sharmila & Santhosh, 2025; Somjai et al., 2020; Suhatmi et al., 2024; Sun et al., 2026).

Moreover, the labor market literature emphasizes the different impacts of AI on the workforce. It can be a substitute for routine tasks, but at the same time, it can complement analytical, creative, managerial, and digitally intensive activities (Appaiah, 2026; Bian, 2024; Choi & Leigh, 2024; Cui, 2025; Liang et al., 2025; Song, 2024; Zhuang, 2025). Hence, employees who have higher digital and transferable skills tend to benefit more from complementary activities, whereas those employees whose tasks can be automated are at a greater risk of displacement (Acemoglu et al., 2022; Aswani, 2026; Chen et al., 2022; Chhibber et al., 2025; Davidescu et al., 2025; Frank et al., 2019; Georgieff & Hye, 2022; Maria et al., 2025; Nigar et al., 2025; Pandey, 2025; Qu, 2025; Shengelia, 2025; Socol et al., 2024; Xie et al., 2021).

Adequate digital infrastructure, connectivity, computer capabilities, data, and human capital constitute neither sufficient nor necessary conditions for the diffusion of AI in a small open economy (Challoumis, 2025a). A country could have all the necessary digital inputs and yet lag behind in terms of implementation of AI in enterprises due to the high costs, riskiness, and business relevance associated with AI initiatives. The findings provided later in this paper are an example of such cases: Cyprus is near the EU average in several readiness indicators and slightly above it in terms of the share of ICT specialists, while being below average in enterprise AI implementation.

Another element of the adoption environment is regulation. Regulation (EU) 2024/1689, the Artificial Intelligence Act, creates a risk-based approach that distinguishes prohibited uses, high-risk uses, uses requiring transparency, and low-risk uses. While regulation may make things more difficult for businesses in terms of compliance and risk management, it can also remove some ambiguity around the lawful use of AI. The economic impact may therefore depend on the industry and the organization (Barac & Rodríguez, 2026; Bostan, 2025; Coletti et al., 2025; Floridi, 2021; Gstrein et al., 2024; Justo-Hanani, 2022; Krarup & Horst, 2023; Mügge, 2023, 2024; Outeda, 2024; Papyshv & Chan, 2026; Papyshv & Yarime, 2023; Roberts et al., 2022; Roberts et al., 2023; Ulnicane, 2022; Walter, 2024). Related work also examines the adoption and governance of artificial intelligence within

the public sector and public services (Chabanna, 2025; Noordt & Misuraca, 2022; Schmidt et al., 2024; Van Noordt et al., 2023).

The literature on Cyprus has so far focused on digital transformation strategy, sector opportunities, challenges to adoption, and comparative indicators. Macroeconomic studies at country level have been sparse, while panel estimates across countries might obscure the particular production structure and fragility of a small island economy (Chaloumis, 2025b). The current study addresses this shortcoming by relying exclusively on annual data for Cyprus and by distinguishing technological capability from enterprise AI adoption. High-technology exports account for knowledge-intensive production and technological sophistication, while merchandise trade and inflation represent key external and macroeconomic factors.

The empirical expectation is purposely conservative. While technological ability may be positively related to growth through innovation, efficiency, and competitiveness, the direction and timing of the relationship are not guaranteed within a short annual data series. High-technology exports may be unstable in a small manufacturing economy, international trade can reflect external demand shocks and foreign supply shocks, and inflation may occur during economic expansion while reducing economic activity in future periods. The empirical methodology therefore uses current and one-lag variables, considers coefficient robustness across sequentially changing models, includes a COVID-19 variable, and conducts an exclusions test.

3. Materials and Methods

In terms of the empirical design, there is an integration of descriptive statistics along with a macroeconometric analysis at the country level. The yearly data were obtained mainly from the World Bank's World Development Indicators, while DESI, Eurostat figures on AI adoption in enterprises, and ICT employment figures have been considered for the context. These descriptive series span the period 1993–2024 wherever available. Since the high-tech exports series starts in 2007 and there is a lag of one year in the regressions, the common estimation period is 2008–2024, which means seventeen years of observations.

Annual GDP growth is the dependent variable. High-technology exports, measured as a percentage of manufactured exports, are used as an indirect proxy for technological sophistication and AI-related absorptive capacity. Merchandise trade as a percentage of GDP captures the openness of the Cypriot economy, while inflation, measured by the GDP deflator represents macroeconomic price conditions. Current and one-period-lagged terms are included because these variables may be associated with contemporaneous growth and delayed adjustment. The sequential specifications are defined as follows:

$$GDPGrowth_t = \alpha + \beta_1 HighTech_t + \beta_2 HighTech_{t-1} + \varepsilon_t. \quad (1)$$

$$GDPGrowth_t = \alpha + \beta_1 HighTech_t + \beta_2 HighTech_{t-1} + \beta_3 Trade_t + \beta_4 Trade_{t-1} + \varepsilon_t. \quad (2)$$

$$GDPGrowth_t = \alpha + \beta_1 HighTech_t + \beta_2 HighTech_{t-1} + \beta_3 Trade_t + \beta_4 Trade_{t-1} + \beta_5 Inflation_t + \beta_6 Inflation_{t-1} + \varepsilon_t. \quad (3)$$

Equation (1) is the baseline technological capability model. Equation (2) adds the current and lagged trade terms, and Equation (3) is the preferred distributed lag specification because it additionally controls for current and lagged inflation. Introducing the variable groups sequentially makes it possible to evaluate whether the estimated high-technology export relationship remains qualitatively stable as economically relevant controls are added.

$$COVID_t = 1 \text{ for } 2020 \text{ or } 2021, \text{ and } 0 \text{ otherwise.} \quad (4)$$

$$\begin{aligned}
 GDPGrowth_t = & \alpha + \beta_1 HighTech_t + \beta_2 HighTech_{t-1} + \beta_3 Trade_t \\
 & + \beta_4 Trade_{t-1} + \beta_5 Inflation_t + \beta_6 Inflation_{t-1} \\
 & + \delta COVID_t + \varepsilon_t.
 \end{aligned}
 \tag{5}$$

Equation (5) augments the preferred specification with a pandemic indicator for 2020–2021. A further sensitivity model re-estimates Equation (3) after excluding both pandemic years. The indicator and the exclusion check serve different purposes: the former retains the full sequence of annual observations, whereas the latter shows how strongly the estimated coefficients depend on the contraction in 2020 and the rebound in 2021. These specifications are not selected on the basis of statistical significance.

All models are estimated by ordinary least squares. The point estimates were obtained in Gretl, robust inference was computed in Python, and the full replication code, together with the embedded estimation data, is provided in Appendix B. Given the limited number of annual observations, inference is based on heteroskedasticity-consistent HC3 standard errors, which apply a stronger small-sample leverage correction than conventional heteroskedasticity-robust estimators. The reported diagnostics include the number of observations, residual degrees of freedom, R^2 , adjusted R^2 , the model F-statistic, its p value, and the Durbin–Watson statistic. These diagnostics are descriptive aids and should not be interpreted as eliminating specification uncertainty.

The coefficient estimates are interpreted as conditional statistical associations. High-technology exports do not directly measure the use of AI by Cypriot enterprises, and the annual sample is too short to support strong causal claims, extensive lag structures, or highly parameterized dynamic models. Complementary DESI, enterprise AI use, and ICT employment indicators are therefore used to contextualize the technological capability proxy, while the limitations created by proxy measurement, sample size, and potential omitted variables are addressed explicitly in the Discussion.

For reporting purposes, Model 1 corresponds to Equation (1), Model 2 to Equation (2), Model 3 to Equation (3), Model 4 to Equation (5), and Model 5 to Equation (3) estimated after excluding 2020 and 2021. The preferred substantive interpretation is based on the pattern across models rather than on a single coefficient or significance threshold.

4. Results

For the Cyprus economy, based on Table 1, the data by sector are as follows:
The results are as follows:

Figure 1 presents a composite readiness proxy calculated as the equal-weighted average of standardized mobile subscriptions per 100 people and high-technology exports as a share of manufactured exports. Positive values indicate that the combined indicator is above its 2015–2023 mean, while negative values indicate below-average conditions within the same period. The proxy improves in 2018–2019, falls sharply in 2020, and recovers from 2021 onward. It should not be interpreted as a direct measure of AI adoption or as a cross-country index. The equal weighting is a transparent descriptive choice rather than an empirically established weighting structure, and future research could compare alternative constructions using cloud adoption, ICT investment, digital intensity, or direct enterprise AI use data.

Table 1. Selected macroeconomic indicators for Cyprus (World Bank Group, 2025).

Series Name	1990 [YR1990]	2000 [YR2000]	2015 [YR2015]	2016 [YR2016]	2017 [YR2017]	2018 [YR2018]	2019 [YR2019]	2020 [YR2020]	2021 [YR2021]	2022 [YR2022]	2023 [YR2023]
Population, total	788,351	947,667	1,219,502	1,237,112	1,254,275	1,270,737	1,286,671	1,302,247	1,317,309	1,331,370	1,344,976
Population growth (annual %)	1.396268	1.749259	1.462131	1.433705	1.377809	1.303933	1.246122	1.203297	1.149979	1.061747	1.016768
Surface area (sq. km)	9250	9250	9251	9251	9251	9250	9250	9250	9250	9250	...
Population density (people per sq. km of land area)	85.31937	102.5614	131.9807	133.8866	135.744	137.5256	139.2501	140.9358	142.5659	144.0877	...
GNI, Atlas method (current US\$)	5.4×10^9	9.84×10^9	2.21×10^{10}	2.12×10^{10}	2.15×10^{10}	2.4×10^{10}	2.54×10^{10}	2.43×10^{10}	2.73×10^{10}	3.01×10^{10}	3.06×10^{10}
GNI per capita, Atlas method (current US\$)	9300	14,180	26,090	24,840	25,020	27,570	28,840	27,280	30,270	33,020	32,960
GNI, PPP (current international \$)	7.69×10^9	1.35×10^{10}	2.69×10^{10}	2.93×10^{10}	3.2×10^{10}	3.43×10^{10}	3.77×10^{10}	3.61×10^{10}	4×10^{10}	4.7×10^{10}	4.8×10^{10}
GNI per capita, PPP (current international \$)	13,260	19,460	31,720	34,460	37,250	39,450	42,700	40,440	44,460	51,500	51,730
Life expectancy at birth, total (years)	76.044	77.9	81.464	81.534	81.543	81.556	81.454	81.23	80.573	80.434	81.648
Fertility rate, total (births per woman)	2.402	1.638	1.323	1.357	1.323	1.319	1.33	1.361	1.392	1.393	1.389
Urban population growth (annual %)	2.019577	1.925564	1.335296	1.336556	1.310459	1.265007	1.238734	1.22714	1.202385	1.143993	1.130277
GDP (current US\$)	5.59×10^9	9.99×10^9	1.99×10^{10}	2.1×10^{10}	2.29×10^{10}	2.58×10^{10}	2.62×10^{10}	2.56×10^{10}	3.04×10^{10}	3.09×10^{10}	3.39×10^{10}
GDP growth (annual %)	7.404	5.965304	3.41892	6.573591	5.750832	6.271664	5.875596	−3.22063	11.38819	7.204868	2.76391
Inflation, GDP deflator (annual %)	5.433125	2.743451	−0.75423	−0.57474	1.020394	1.025754	1.350086	−1.20792	3.04273	6.709267	3.812218
Exports of goods and services (% of GDP)	51.50056	69.96282	70.0173	70.48405	73.83648	74.51113	75.75887	79.64725	90.75783	105.6218	97.15785
Imports of goods and services (% of GDP)	57.10764	67.53208	67.25912	68.53805	74.17688	73.11243	74.7473	81.02146	86.0699	102.0107	96.11077
Gross capital formation (% of GDP)	27.04543	20.42916	13.32268	17.05415	20.38246	18.94647	19.49417	20.65146	19.64568	20.2708	20.64125
Revenue, excluding grants (% of GDP)	27.62766	32.88632	40.42487	38.32424	38.41242	38.31795	39.32079	38.37329	38.25679	38.42544	41.25911
Tax revenue (% of GDP)	18.02989	20.79663	24.04739	23.51606	23.81988	23.83345	23.0748	21.94011	22.55228	23.16304	24.08231
Military expenditure (% of GDP)	7.374036	2.82209	1.647668	1.404558	1.568103	1.760546	1.786619	1.920172	1.83792	1.822731	1.824603
High-technology exports (% of manufactured exports)	...	...	12.71082	13.32851	13.34996	19.85679	19.87422	12.24483	15.969	17.6596	18.5213
Merchandise trade (% of GDP)	62.93897	48.03799	51.82508	51.29128	54.55717	61.60984	48.02138	46.26866	47.27939	54.06399	56.52622

Figure 2 depicts pre-pandemic growth expansion, followed by growth contraction during the pandemic and then recovery via two steps followed by growth moderation. Thus, from 2015 to 2019, the economy expands at a rate of $3\frac{1}{2}$ – $6\frac{1}{2}$ %, reflecting normal growth in the service sectors (tourism, financial services, and logistical). In 2020, the country experiences a growth collapse, with a negative growth of about -3.2% , as expected given the COVID-19 shock. This followed by a growth bounce to 11.4% in 2021 as a result of recovering and arithmetic base-year considerations. Growth then normalizes in 2022 and 2023. Namely, economic growth slows to 7.2% in 2022 as the recovery in tourism and trade continues, before declining to about 2.8% as conditions become tougher. In the regression analysis, this volatility is important to consider because the growth dynamics of 2020–2021 dominate short-run regressions. Consequently, a simple association between an AI variable and GDP may be affected by dynamics of the pandemic and changes in external demands (Challoumis, 2025c, 2025d).

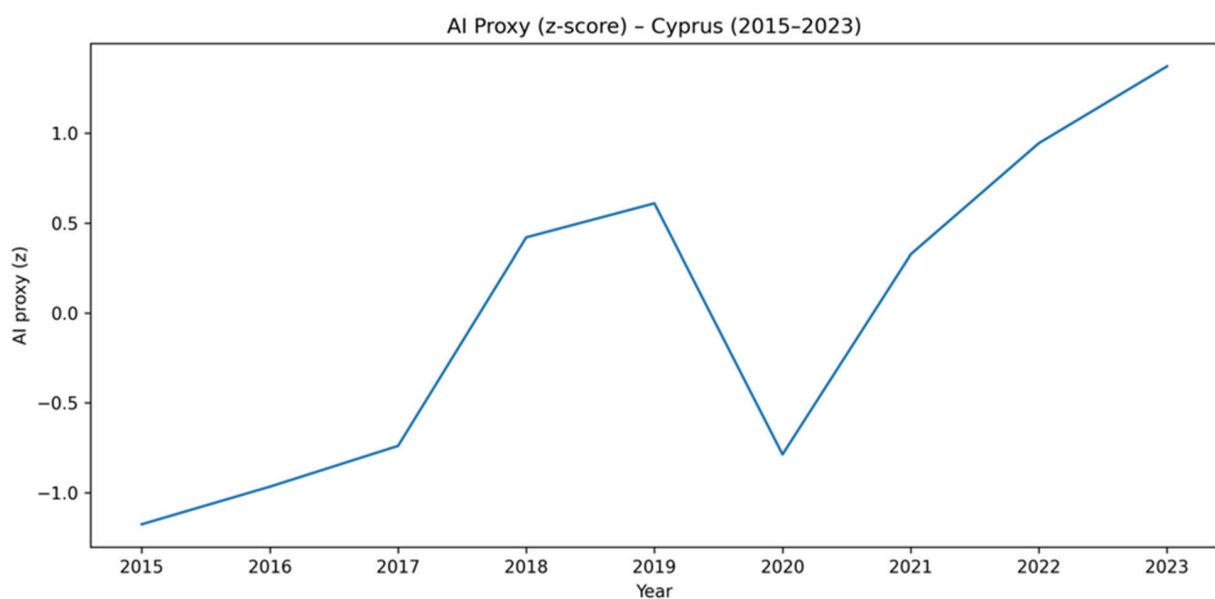


Figure 1. Composite AI readiness proxy for Cyprus, 2015–2023 (authors’ calculations; see Appendix A).

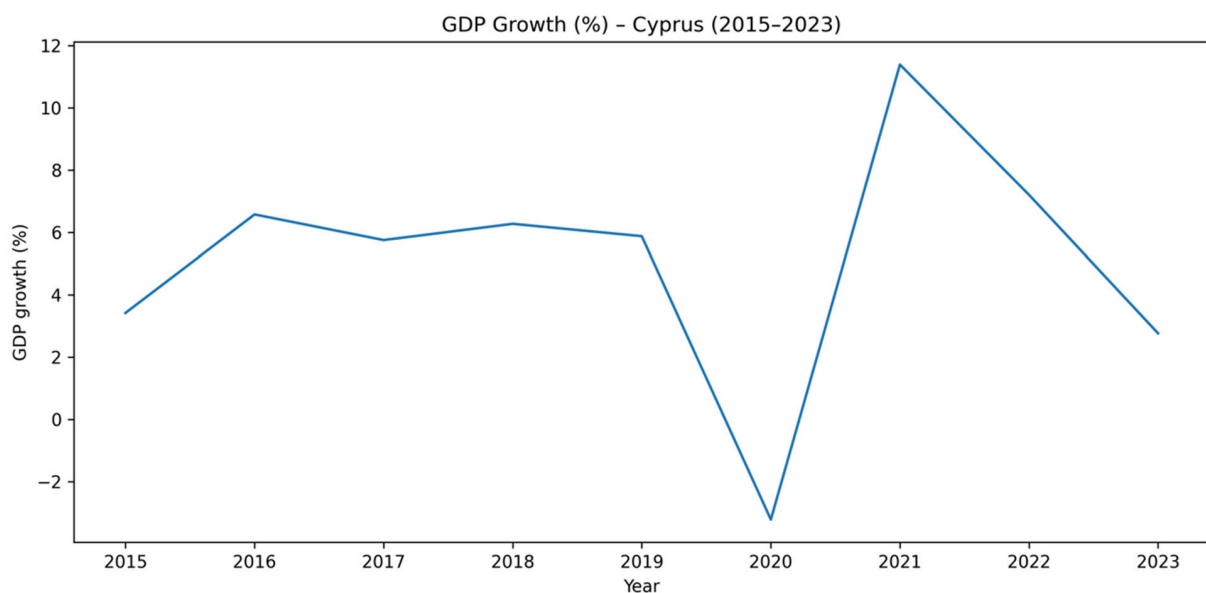


Figure 2. Annual GDP growth in Cyprus, 2015–2023 (authors’ calculations; see Appendix A).

Figure 3 captures high-technology exports as a percentage of Cyprus's manufactured exports. From 2015 to 2017, the percentage remains constant at 12.6–13.4%, indicating that high technology makes up a very modest percentage of the small-scale manufacture sector. Between 2018 and 2019, however, the step increases to around 20%, indicating a possible shift from more ordinary manufactured goods to technologically advanced products (for example, electronics, medicines and other pharmaceutical products, precision mechanical equipment, among others). Given the small size of the manufacturing industry in Cyprus, a few product lines could be enough to affect the percentage dramatically. However, the ratio drops to about 12% in 2020, which corresponds with disruption in supply chains and declines in certain categories of high-tech products caused by the COVID-19 pandemic. The ratio regains its lost ground from 2021, standing at 16% in 2021 and between 18% and 18.5% in 2022–2023, just below its previous year's record. It is an indicator of technological intensity and absorptive capacity: the higher the high-tech percentage, the greater the chances for adoption due to the relevant skills and supply–demand chain links. However, one should use this measure with caution since it is a ratio and may change not because of changes in either the numerator or the denominator. Furthermore, volatility can be an issue due to the small size of the country in question, and the indicator applies to manufacturing alone, while Cyprus is a services-based economy.

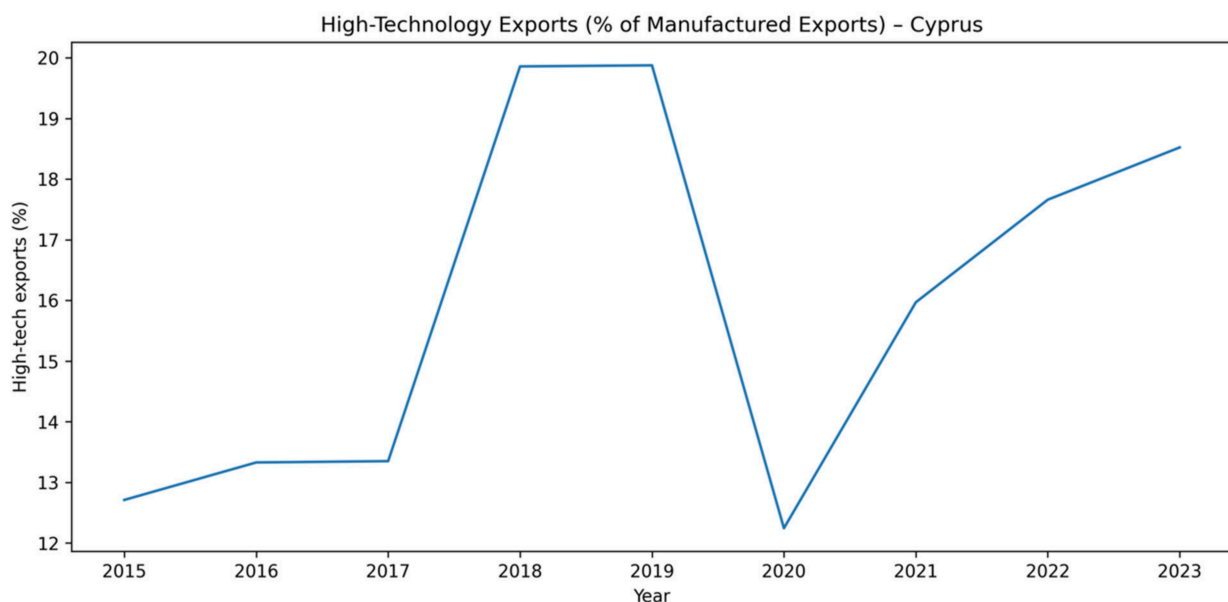


Figure 3. High-technology exports as a share of manufactured exports in Cyprus (authors' calculations; see Appendix A).

Figure 4 illustrates the high degree of openness of the Cypriot economy. Exports and imports rise markedly as shares of GDP during the period and move closely together, reflecting the importance of international services, trade linkages, imported inputs, and global value chains. The ratios are further affected by changes in nominal GDP and therefore should not be regarded as volume indicators alone. With respect to the econometric exercise, the variable for merchandise trade is employed as the openness indicator; thus, the coefficients for the technological capability ratio can be interpreted in the context of a high level of exposure to external activities.

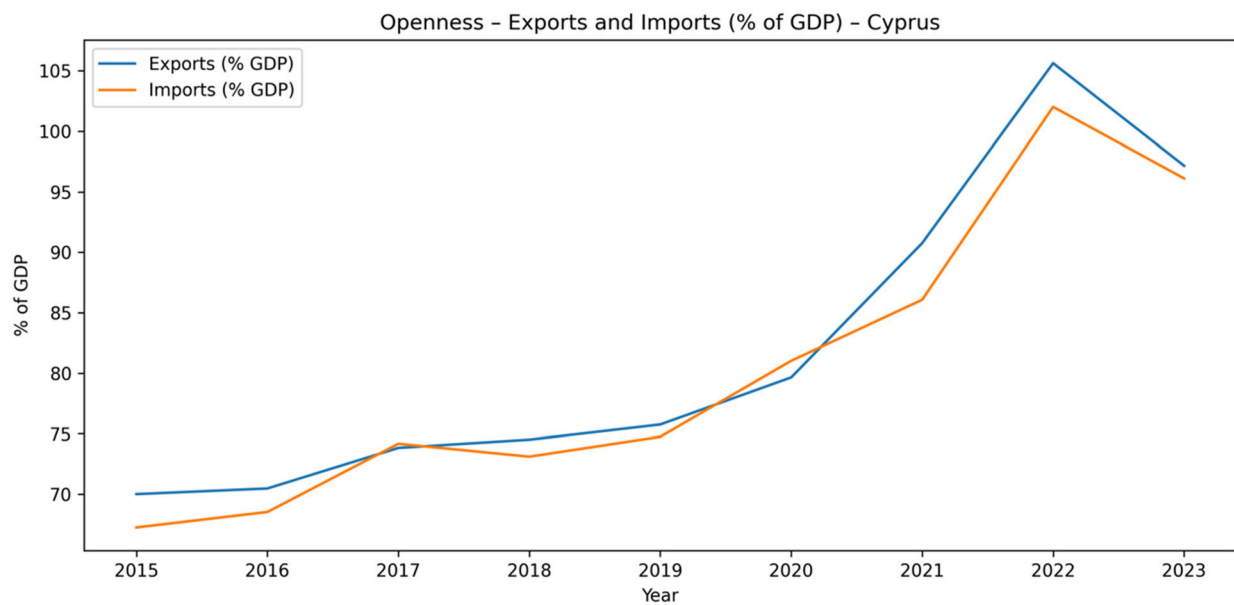


Figure 4. Exports and imports of goods and services as percentages of GDP in Cyprus (authors' calculations; see Appendix A).

Figure 5 places the shorter digital and econometric metrics within the larger picture of socioeconomic development in Cyprus. The trend for population, income, and life expectancy is upwards during the period, whereas the fertility rate trends downwards. Annual regressions based on short samples can be highly susceptible to exceptional data.

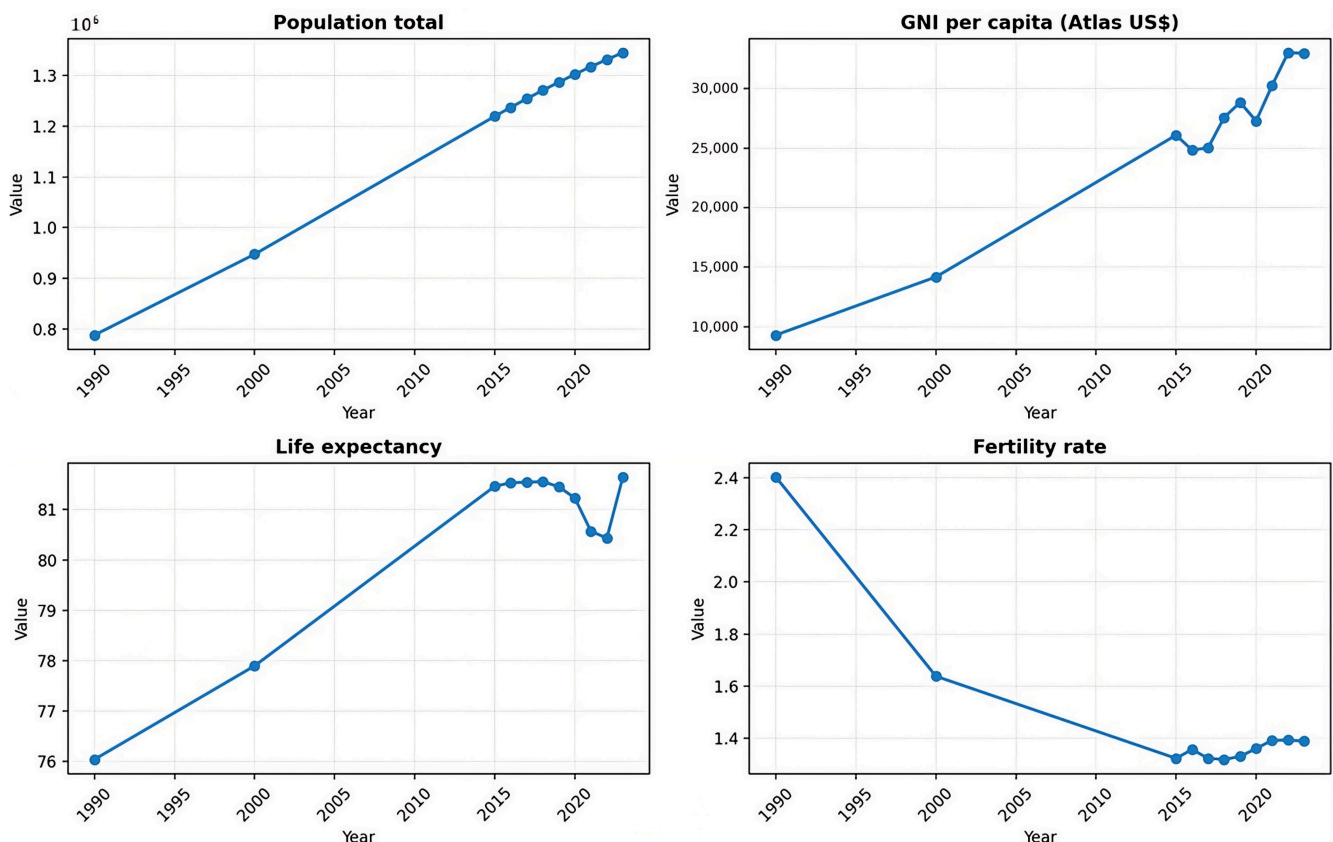


Figure 5. Long-term socioeconomic trends in Cyprus, 1990–2024 (authors' calculations).

The trends shown in Figure 5 can be regarded as contextual rather than causative. They show that there was continuous economic and social growth in tandem with demographic aging challenges and macroeconomic shocks (Challoumis & Eriotis, 2025). While such context could affect labor supply, skill demand, investments, and the adoption of new technologies, they are not included in the regression as regressors due to the limited number of observations in the sample set.

While the AI readiness proxy used in this analysis is calculated using the data on mobile-cellular subscriptions and high-technology exports, there are other metrics that could be used to give a more comprehensive picture of the extent of digital transformation and artificial intelligence adoption in Cyprus. Specifically, DESI and Eurostat statistics on AI adoption in enterprises, and ICT employment indicators could be used as supplementary sources of information on digital capability, technological readiness, and AI technology diffusion. A comparison between Cyprus and the European Union averages is provided in Table 2.

Table 2. Additional indicators of AI readiness in Cyprus (Cyprus Mail, 2022; European Commission, 2024; Eurostat, 2025e).

Indicator	Latest Available Value
DESI—Integration of Digital Technology	35.3 (out of 100) vs. EU-27 average of 36.1—ranked 17th of 27. In terms of human capital, Cyprus ranked 21st with a score of 41.8, compared with the EU27 average of 45.7. For connectivity, it ranked 12th with a score of 58.8, compared with the EU27 average of 59.9. For the integration of digital technology, it ranked 17th with a score of 35.3, compared with the EU27 average of 36.1.
Enterprises Using AI Technologies (%)	9.3% (2025), compared with an EU average of approximately 20%, indicating considerable room for further enterprise adoption.
ICT Specialists (% of Employment)	5.4% (2023) vs. EU average of 4.8%. ICT specialists make up 5.4% of employment in the Cypriot population, above the EU average (4.8%). This is a remarkable annual growth of 17.4%, well above the EU average annual growth of 4.3%.

Complementary variables representing the level of digitization and AI adoption in Cyprus are provided in Table 3. They are not considered in the econometric model but are presented to give an additional perspective for the interpretation of the AI readiness proxy. Thus, the following table summarizes these indicators:

Table 3. Complementary indicators of artificial intelligence readiness and digital transformation in Cyprus relative to the European Union average (authors' table).

Indicator	Cyprus	EU Average	Year	Unit
DESI—Integration of Digital Technology	35.3	36.1	2022	out of 100
Enterprises Using AI Technologies (%)	9.3	20.0	2025	%
ICT Specialists (% of Employment)	5.4	4.8	2023	% of employment

Note: The “DESI—Integration of Digital Technology” indicator (0–100 composite score) was discontinued by the European Commission after the 2022 DESI edition. From 2023 onward, this dimension was restructured and absorbed into the “Digitalization of Businesses” pillar of the annual State of the Digital Decade reports, which comprises different sub-indicators (e.g., enterprise adoption of AI, cloud computing, and big data; e-commerce uptake; and SME digital intensity) rather than a single comparable score. Consequently, the value reported here reflects the last published edition of this specific composite metric and is not methodologically comparable with the 2023–2025 figures reported elsewhere in this table (e.g., AI enterprise adoption and ICT specialists). Therefore, this indicator should be interpreted as complementary descriptive evidence of Cyprus's digital business integration before 2023 rather than as a directly comparable measure with the 2023–2025 indicators reported elsewhere in this table.

As a whole, the combination of the two sets of complementary indices presented in Table 3 helps differentiate between digital readiness and AI deployment. In terms of the former DESI business digitalization index and the share of ICT specialists, Cyprus lags only marginally behind the average EU level, whereas when it comes to the number of businesses employing AI technologies, Cyprus does not yet match the average EU level. It seems that there might be other obstacles preventing readiness from being converted into AI deployment, rather than a simple lack of connection and a digitally skilled workforce.

Figure 6 compares Cyprus with the EU average using three distinct indicators. Cyprus is slightly below the EU average in the final DESI Integration of Digital Technology score, below it in enterprise AI adoption, and slightly above it in the share of ICT specialists in employment. The figure therefore reinforces the distinction between enabling inputs and realized adoption: a comparatively strong skills indicator has not yet translated into widespread firm-level use of AI technologies.

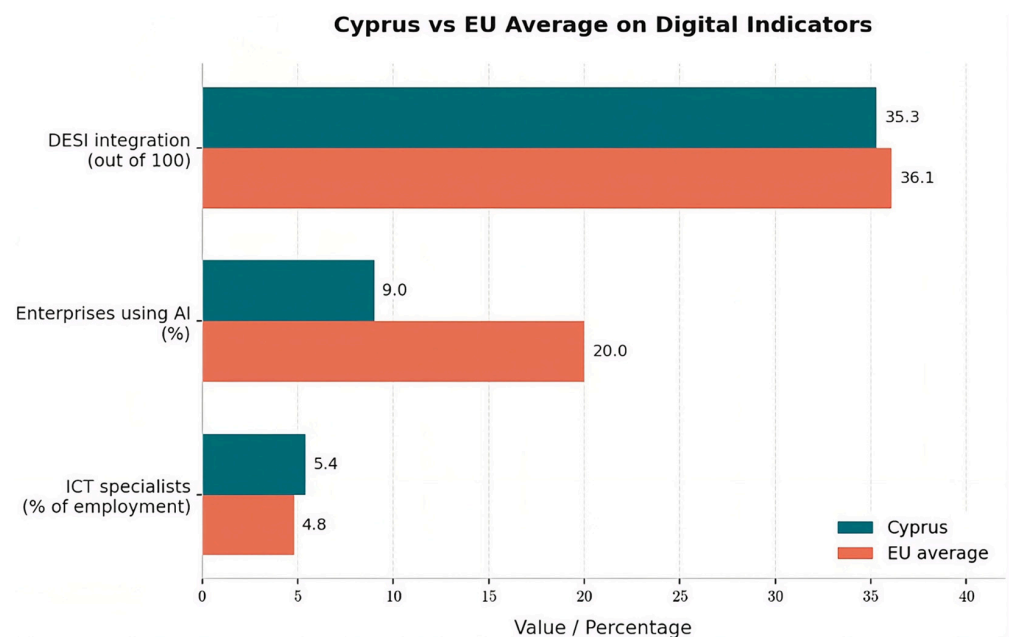


Figure 6. Selected digital readiness and AI adoption indicators: Cyprus and the EU average (authors' results).

Table 4 includes Malta as an important comparator from a structural perspective. Cyprus is doing quite well in terms of social media usage and low-intensity use of digital technologies. The share of paid use of clouds is also near the EU average, whereas enterprise AI use has not developed as fast as in Malta's, which shows definite room for catch-up. This case shows that smallness, insularity, and dependency on tourism do not by themselves dictate the outcome of adoption processes. Different capacities of firms, investment incentives, and the existence of infrastructure are plausible mechanisms, but their confirmation needs firm-level data.

In order to conduct the econometric test, the study makes use of the macroeconomic time series variables per year in Cyprus as provided by the World Bank for the years 1993–2024. While the total time series data covers several decades, the high-technology exports indicator—the proxy chosen to reflect AI technological capability—is only available starting from 2007. As such, the econometric test is carried out over the period where all explanatory variables are available. Table 5 shows the time series data for the main variables used in the econometric test: GDP deflator (inflation), high-technology exports as a share of manufactured exports, and merchandise trade as a share of GDP.

Table 4. Digital technology adoption in Cyprus and Malta compared with the EU27 average (authors' table, based on the Eurostat ICT Usage and E-commerce in Enterprises Survey, 2022–2025 editions) (European Commission, 2025; Eurostat, 2024, 2025a, 2025b, 2025c, 2025d, 2025e).

Indicator (Survey Year)	Cyprus	Malta	EU27 Average	Cyprus–Malta Gap (pp)
Enterprises using AI technologies, % (2025)	9.3	17.3	20.0	−8.0
Enterprises using paid cloud computing services, % (2025)	51.4	74.9	52.7	−23.5
Enterprises using social media, % (2024)	79.9	>80 ^a	63.6	≈−1 to −8
Enterprises reaching at least a basic level of digital intensity/digital technology adoption, % (2022–2025) ^b	67.0	81.3	56.0	−14.3
Enterprises reaching a very high level of the Digital Intensity Index, % (2024)	n/a ^c	11.4	≈8–9	n/a ^c

Note: All data are for enterprises with 10 or more employees and self-employed persons, which constitute the standard Eurostat survey population, unless otherwise noted. (a) Malta is reported among a group of five EU countries exceeding 80% social media use in 2025 (alongside Denmark, the Netherlands, Sweden, and Belgium); however, a precise point estimate for Malta alone was not located, so the Cyprus–Malta gap for this row is approximate. (b) The definitions of the “basic level of digital intensity/adoption” differ slightly by year and source (Digital Intensity Index basic threshold vs. the broader Digital Decade “basic level of digital technology adoption” measure). Therefore, this row should be read as indicating relative standing rather than as a single harmonized indicator. (c) There is no mention of Cyprus with a “very high DII” leader countries in Eurostat figures. It does not indicate a score of zero but simply implies that Cyprus is not one of the mentioned countries.

Table 5. Macroeconomic variables used in the econometric analysis of the Cypriot economy (1993–2024) (World Bank Group, 2025).

Series Name	Inflation, GDP Deflator (Annual %)	High-Technology Exports (% of Manufactured Exports)	Merchandise Trade (% of GDP)
1993	4.803133	...	51.59104
1994	5.270982	...	53.66495
1995	13.59785	...	49.52111
1996	2.640973	...	53.63609
1997	2.236885	...	51.373
1998	1.965681	...	46.30868
1999	2.301976	...	43.96114
2000	2.743451	...	48.03799
2001	3.660292	...	47.11529
2002	0.296378	...	43.16026
2003	5.387684	...	37.0446
2004	2.709299	...	37.239
2005	2.019525	...	42.21139
2006	3.086106	...	41.15529
2007	4.138054	31.29566	41.75858
2008	4.734624	32.01724	44.09106
2009	0.262899	32.52943	34.90455
2010	1.881382	38.20152	38.64738
2011	1.616255	30.35854	37.97182
2012	1.678774	16.5915	36.07555
2013	−0.93774	13.0834	34.77921
2014	−1.33827	14.52826	48.04546
2015	−0.75423	12.71082	51.82508
2016	−0.57474	13.32851	51.29128
2017	1.020394	13.34996	54.55717
2018	1.025754	19.85679	61.60984
2019	1.350086	19.87422	48.02138
2020	−1.20792	12.24483	46.26866
2021	3.034063	15.969	47.27939
2022	6.620597	17.6596	53.57479
2023	5.601703	18.74195	54.61089
2024	3.121999	18.03292	47.14553

Table 5 summarizes the explanatory variables over 1993–2024. High-technology exports are available from 2007; therefore, the inclusion of one-period lags determines a common regression sample of 2008–2024. The series display substantial variation: high-technology exports fall sharply after 2010 before recovering, merchandise trade changes with external conditions, and inflation ranges from deflationary episodes to the post-pandemic increase. The 2020 and 2021 observations are retained in the primary models and are addressed explicitly through the COVID-19 indicator and the exclusion-based sensitivity model. Minor differences between Tables 1 and 5 for the most recent years reflect revisions across successive World Bank data downloads; the econometric analysis uses the values reported in Table 5.

Table 6 reports the sequential distributed lag estimates. Model 1 includes current and lagged high-technology exports; Model 2 adds current and lagged merchandise trade; Model 3 adds current and lagged inflation and is the preferred specification; Model 4 adds the COVID-19 indicator; and Model 5 re-estimates Model 3 after excluding 2020 and 2021. Coefficients are shown with HC3 standard errors in parentheses.

Table 6. Sequential distributed lag OLS estimates for annual GDP growth in Cyprus (authors' calculations using Gretl, 2026b; see also Appendix B).

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	5.3137 (3.1419)	−18.3122 (18.3840)	−12.0931 (9.6008)	−12.7533 (11.9497)	−18.9791 * (8.3516)
HighTech _t	0.5008 ** (0.1985)	0.3730 (0.2282)	0.2838 * (0.1309)	0.2914 (0.1704)	0.2057 (0.1173)
HighTech _{t−1−1}	−0.6122 *** (0.1943)	−0.2795 (0.3802)	−0.2392 (0.1856)	−0.2356 (0.2634)	−0.0845 (0.1710)
Trade _t	—	0.2425 (0.3036)	−0.0248 (0.2011)	−0.0112 (0.2689)	0.1263 (0.2168)
Trade _{t−1−1}	—	0.1731 (0.1324)	0.3255 (0.1920)	0.3188 (0.2055)	0.2857 (0.1741)
Inflation _t	—	—	1.4765 *** (0.3464)	1.4518 ** (0.5989)	1.0498 ** (0.4128)
Inflation _{t−1−1}	—	—	−1.3519 ** (0.4568)	−1.3157 * (0.6041)	−0.9989 * (0.4705)
COVID _t	—	—	—	0.7748 (4.8462)	—

Note: The dependent variable is annual GDP growth. HC3 standard errors are reported in parentheses. Model 5 excludes 2020 and 2021. Significance indicators are based on two-sided *t*-tests: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$. HighTech denotes high-technology exports (% of manufactured exports), Trade denotes merchandise trade (% of GDP), and Inflation denotes the GDP deflator inflation rate.

The sequence of models shows that coefficient interpretation depends on the included controls. In Model 1, current high-technology exports are positively associated with growth, while the lagged term is negative. After trade and inflation are introduced, the contemporaneous high-technology coefficient remains positive but becomes statistically marginal in the preferred Model 3, whereas the lagged coefficient remains negative and is estimated imprecisely. The contemporaneous trade coefficient is close to zero in Model 3, while the lagged trade coefficient is positive but does not reach conventional significance at the 10% level when small-sample *t* inference is used. Inflation displays the clearest distributed lag pattern: its current coefficient is positive, whereas its lagged coefficient is negative. These opposite signs are consistent with inflation accompanying current nominal expansion while being associated with weaker subsequent real growth; however, the estimates do not establish a causal mechanism.

Substituting the Model 3 coefficients into Equation (3) gives the preferred fitted specification:

$$\begin{aligned}\hat{GDPGrowth}_t = & -12.0931 + 0.2838HighTech_t - 0.2392HighTech_{t-1} \\ & -0.0248Trade_t + 0.3255Trade_{t-1} + 1.4765Inflation_t \\ & -1.3519Inflation_{t-1}.\end{aligned}\quad (6)$$

With the pandemic indicator included, the fitted equation is:

$$\begin{aligned}\hat{GDPGrowth}_t = & -12.7533 + 0.2914HighTech_t - 0.2356HighTech_{t-1} \\ & -0.0112Trade_t + 0.3188Trade_{t-1} + 1.4518Inflation_t \\ & -1.3157Inflation_{t-1} + 0.7748COVID_t.\end{aligned}\quad (7)$$

Equation (6) presents the baseline specification linking GDP growth to high-technology exports, trade, and inflation, including their lagged values. Equation (7) extends this model by introducing the COVID-19 dummy variable to control for the effects of the pandemic on GDP growth. Table 7 summarizes the diagnostic and goodness-of-fit statistics for the five estimated models.

Table 7. Model fit and robustness statistics for the sequential specifications (authors' calculations using Gretl, 2026b; see also Appendix B).

Statistic	Model 1	Model 2	Model 3	Model 4	Model 5
Observations (N)	17	17	17	17	15
Residual degrees of freedom	14	12	10	9	8
R ²	0.4032	0.6095	0.9253	0.9278	0.9320
Adjusted R ²	0.3180	0.4794	0.8805	0.8717	0.8811
F-statistic	4.9955	3.2093	10.9525	7.2463	8.9687
Probability (F-statistic)	0.0230	0.0522	0.0007	0.0042	0.0034
Durbin–Watson statistic	1.6295	2.0795	2.1860	2.0733	2.0756

Model 3 has an R² = 0.9253 and an adjusted R² = 0.8805, with a Durbin–Watson statistic of 2.1860. The introduction of the COVID-19 dummy does little to improve R², reduces the adjusted R², and does not change the pattern of the substantive regression coefficients significantly. The coefficient on the COVID-19 dummy is small relative to the HC3 standard error and is statistically insignificant. Removal of 2020 and 2021 retains a positive coefficient on current high technology, lagged trade, and differently signed inflation coefficients, but uncertainty persists. This stability of signs is encouraging, but the very high fit needs to be interpreted carefully due to the limited sample size and number of distributed lags.

Figure 7 compares observed annual GDP growth with the values fitted by the preferred regression. It is a goodness-of-fit visualization rather than a graph of GDP growth against a single explanatory variable.

The observations in Figure 7 are mainly spread along the 45-degree line, showing that the model being preferred is able to explain a lot of the yearly variability that can be seen in the data sample. Some observations still lie far away from the line, which is normal in a volatile small open economy, as well as in a model that leaves out several determinants of growth (Challoumis et al., 2025a). The figure above thus confirms the in-sample performance, but it does not confirm causality, out-of-sample forecasting performance, or that high-tech exports measure AI adoption.

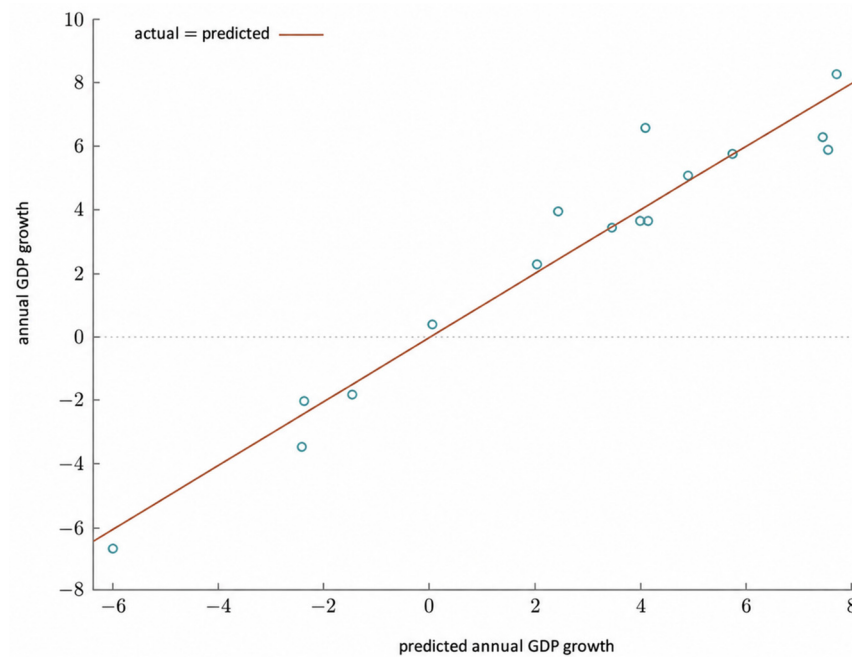


Figure 7. Actual versus predicted annual GDP growth from the preferred distributed lag model (authors' calculations).

5. Discussion

It is important to consider the empirical evidence in light of the general body of evidence indicating that AI-driven productivity increases do not occur equally among all countries and firms. Factors such as digital infrastructure, skills, financial capability, management capabilities, data availability, cloud computing, and regulatory preparedness determine how much potential can actually translate into productivity. Cyprus is an example where the digital inputs are generally good, but AI usage in businesses has still not hit the EU average level (Chaar et al., 2025; Dahlke et al., 2024; Djeffal et al., 2022; Schwaewe et al., 2024).

The distributed lag results do not lend themselves to a straightforward unidirectional story. The contemporaneous positive coefficient and the lagged negative coefficient on high-technology exports imply that yearly movements in this ratio could also be influenced by time, composition, and denominator effects. Likewise, the low contemporaneous trade coefficient and the higher lagged trade coefficient seem consistent with the lagged nature of the relationship with external activity; however, there is insufficient certainty to come to a definitive conclusion in this regard. The current positive and lagged negative coefficients on the inflation variable are fairly robust through the various specifications, implying that price considerations are strongly related to the growth cycle. Most significantly, the COVID-19 dummy is irrelevant and does not influence the coefficient pattern at all; this simply indicates that the dummy explains little of the variation in growth conditional on the other variables included in the regression.

Consequently, the policy implications stem from both the descriptive and econometric findings rather than from any one individual coefficient. In particular, there is a need for Cyprus to adopt policies that support firm capabilities for the actual implementation of digital technology, such as supportive policies for small business experimentation, access to cloud and data infrastructures, training for managers and workers, linkages between universities and firms, and regulatory clarity. Given the openness of its economy, innovation policies also have to be associated with export capabilities, international business links, and the commercialization of know-how-intensive services. The sectoral focus does not have to stop at tourism and transport, ICT, financial services, professional services, health

care, and public administration might provide more immediate opportunities due to their higher data intensity and digital expertise.

There are some issues to take into account when interpreting the findings. Exports of high technology represent an approximate variable, which includes manufacturing more directly than services, the latter of which constitute the core of the Cypriot economy (Challoumis et al., 2025b, 2026). The annual data sample is relatively small, implying that the coefficient estimates are rather vulnerable to individual observations and do not allow for a large set of control variables, lags, and diagnostics. The models might suffer from problems such as omitted variables, endogeneity, structural breaks, and changes in measurement. Further studies would benefit from employing enterprise surveys, microdata, productivity indicators at the industry level, measures of investments and employment related to AI, cloud computing and usage of data, and longer harmonized time series provided by Eurostat.

6. Conclusions

In this research, an exploratory macroeconomic evaluation is done on the technological capability and economic growth of AI in Cyprus. This involves the use of descriptive data in the long run together with sequential distributed lag methodology between 2008 and 2024. High-technology exports are used as a proxy measure of technological capability and absorptive capacity, with merchandise exports and inflation being the control variables that are used to capture the traits of a small open economy. The chosen model shows a positive contemporaneous relationship and a negative lagged relationship with high-technology exports, with the lagged relationship being stronger than the contemporaneous relationship for merchandise exports, and a positive contemporaneous but negative lagged relationship with inflation.

The descriptive evidence contains an caveat: the country's digital infrastructure and skill set may be relatively advanced, but it has not translated into AI adoption among enterprises at the same pace as in the EU. This means that the crucial policy issue to address will be firm-level diffusion and usage rather than connectivity alone. Assistance to SMEs, advanced cloud and data services, AI-related skills, cooperation between academia and industry, ethical experimentation, and proper implementation of the regulatory framework in the national and European context may contribute towards bridging the gap.

The results still suffer from the problems associated with the proxy measure, yearly aggregation, and the limited sample size. The study does not determine the effect of AI on a causal basis, does not measure productivity at the firm level, and also does not determine what sectors create the observed macroeconomic relationships. The contributions of the study include the development of a framework for country-specific analysis that differentiates technology ability and AI adoption and tests the robustness of the results regarding the lag structure and pandemic data. With increasing data availability, the framework can be expanded to cover sectors, firms, direct adoption, and comparisons among small countries.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

The following Python code reproduces the AI readiness proxy and the descriptive figures (Figures 1–4):

```
# ©© 2025 All Rights Reserved Constantinos Challoumis
# =====
# Cyprus AI-readiness proxy and descriptive figures (2015–2023)
# =====
import os
import zipfile
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from google.colab import files

OUTDIR = "/content/cyprus_results"
os.makedirs(OUTDIR, exist_ok=True)
# -----
# Data
# -----
data = {
    "Year": [1990, 2000] + list(range(2015, 2024)),

    "GDP_growth_pct": [
        7.404, 5.965304, 3.41892, 6.573591, 5.750832,
        6.271664, 5.875596, −3.22063, 11.38819, 7.204868, 2.76391
    ],

    "Exports_GDP_pct": [
        51.50056, 69.96282, 70.0173, 70.48405, 73.83648,
        74.51113, 75.75887, 79.64725, 90.75783, 105.6218, 97.15785
    ],

    "Imports_GDP_pct": [
        57.10764, 67.53208, 67.25912, 68.53805, 74.17688,
        73.11243, 74.7473, 81.02146, 86.0699, 102.0107, 96.11077
    ],

    "Investment_GDP_pct": [
        27.04543, 20.42916, 13.32268, 17.05415, 20.38246,
```

```

        18.94647, 19.49417, 20.65146, 19.64568, 20.2708, 20.64125
    ],

    "Inflation_deflator_pct": [
        5.433125, 2.743451, -0.75423, -0.57474, 1.020394,
        1.025754, 1.350086, -1.20792, 3.04273, 6.709267, 3.812218
    ],

    "Mobile_per_100": [
        0.544701, 31.3009, 130.982, 132.637, 136.172,
        137.045, 139.994, 138.388, 145.992, 151.241, 155.696
    ],

    "HighTech_exports_pct_mf": [
        np.nan, np.nan, 12.71082, 13.32851, 13.34996,
        19.85679, 19.87422, 12.24483, 15.969, 17.6596, 18.5213
    ],

    "GNIpc_PPP": [
        13260, 19460, 31720, 34460, 37250,
        39450, 42700, 40440, 44460, 51500, 51730
    ],
}

df = pd.DataFrame(data)
df = df[df["Year"] >= 2015].copy()
# -----
# AI proxy
# -----
def zscore(x):
    x = pd.Series(x, dtype="float64")
    return (x - x.mean()) / x.std(ddof=0)

df["Mobile_z"] = zscore(df["Mobile_per_100"])
df["HighTech_z"] = zscore(df["HighTech_exports_pct_mf"])

df["AI_proxy_z"] = df[["Mobile_z", "HighTech_z"]].mean(axis=1)
df["AI_proxy_z_lag"] = df["AI_proxy_z"].shift(1)

df["GNIpcPPP_growth_pct"] = 100 * (
    np.log(df["GNIpc_PPP"]) - np.log(df["GNIpc_PPP"].shift(1))
)

df.to_csv(f'{OUTDIR}/cyprus_ai_dataset_2015_2023.csv', index=False)
# -----
# Figures
# -----
def save_and_show(figpath):
    plt.tight_layout()
    plt.savefig(figpath, dpi=300)

```

```

plt.show()
plt.close()

# Figure 1: AI proxy
plt.figure(figsize=(10, 5))
plt.plot(df["Year"], df["AI_proxy_z"], marker="o")
plt.title("AI Proxy (z-score) – Cyprus (2015–2023)")
plt.xlabel("Year")
plt.ylabel("AI proxy (z)")
plt.grid(True, alpha=0.3)
save_and_show(f"{OUTDIR}/fig_ai_proxy.png")

# Figure 2: GDP growth
plt.figure(figsize=(10, 5))
plt.plot(df["Year"], df["GDP_growth_pct"], marker="o")
plt.title("GDP Growth (%) – Cyprus (2015–2023)")
plt.xlabel("Year")
plt.ylabel("GDP growth (%)")
plt.grid(True, alpha=0.3)
save_and_show(f"{OUTDIR}/fig_gdp_growth.png")

# Figure 3: High-tech exports
plt.figure(figsize=(10, 5))
plt.plot(df["Year"], df["HighTech_exports_pct_mf"], marker="o")
plt.title("High-Technology Exports (% of Manufactured Exports) – Cyprus")
plt.xlabel("Year")
plt.ylabel("High-tech exports (%)")
plt.grid(True, alpha=0.3)
save_and_show(f"{OUTDIR}/fig_hightech_exports.png")

# Figure 4: Openness
plt.figure(figsize=(10, 5))
plt.plot(df["Year"], df["Exports_GDP_pct"], marker="o", label="Exports (% GDP)")
plt.plot(df["Year"], df["Imports_GDP_pct"], marker="o", label="Imports (% GDP)")
plt.title("Openness – Exports and Imports (% of GDP) – Cyprus")
plt.xlabel("Year")
plt.ylabel("% of GDP")
plt.legend()
plt.grid(True, alpha=0.3)
save_and_show(f"{OUTDIR}/fig_openness_exports_imports.png")
# -----
# Print output files
# -----
print("\nOutputs directory:", OUTDIR)

for fn in sorted(os.listdir(OUTDIR)):
    p = os.path.join(OUTDIR, fn)
    print("✓", fn, os.path.getsize(p), "bytes")
# -----
# ZIP file

```

```
# -----
zip_path = "/content/cyprus_results_bundle.zip"
with zipfile.ZipFile(zip_path, "w", zipfile.ZIP_DEFLATED) as z:
    for fn in os.listdir(OUTDIR):
        z.write(os.path.join(OUTDIR, fn), arcname=fn)

files.download(zip_path)
```

Appendix B

The following self-contained Python script reproduces the full econometric analysis reported in Tables 6 and 7 and in Equations (6) and (7): the five sequential distributed lag OLS models with heteroskedasticity-consistent HC3 standard errors and small-sample *t* inference. The estimation data (World Bank World Development Indicators for Cyprus, 2007–2024, as reported in Table 5) are embedded in the script, so the output can be verified independently of any statistical package settings. The point estimates are identical to those obtained in Gretl:

```
# © 2026 All Rights Reserved Constantinos Challoumis
# =====
# Appendix B: Replication of Tables 6 and 7 (Models 1–5)
# OLS with heteroskedasticity-consistent HC3 standard errors
# Data: World Bank WDI, Cyprus, 2007–2024 (Table 5)
# =====
import numpy as np
import pandas as pd
import statsmodels.api as sm
from statsmodels.stats.stattools import durbin_watson

years = list(range(2007, 2025))
data = {
    "GDP_growth": [5.098226, 3.646989, -2.015082, 2.282671, 0.416712,
                  -3.447382, -6.587478, -1.776059, 3.41892, 6.573591,
                  5.750832, 6.271664, 5.875596, -3.22063, 11.397559,
                  8.273726, 3.619456, 3.940774],
    "Inflation": [4.138054, 4.734624, 0.262899, 1.881382, 1.616255,
                 1.678774, -0.937739, -1.338266, -0.754231, -0.574742,
                 1.020394, 1.025754, 1.350086, -1.207924, 3.034063,
                 6.620597, 5.601703, 3.121999],
    "HighTech": [31.295656, 32.017237, 32.529426, 38.20152, 30.358544,
                 16.591497, 13.083398, 14.528263, 12.710824, 13.328515,
                 13.349961, 19.856794, 19.874216, 12.244828, 15.969003,
                 17.659598, 18.741953, 18.032923],
    "Trade": [41.75858, 44.091061, 34.90455, 38.647377, 37.971822,
              36.075547, 34.779215, 48.045463, 51.825083, 51.29128,
              54.557172, 61.609844, 48.021376, 46.268662, 47.27939,
              53.574794, 54.610887, 47.145529],
}
df = pd.DataFrame(data, index=years)
df["HighTech_1"] = df["HighTech"].shift(1)
df["Trade_1"] = df["Trade"].shift(1)
df["Inflation_1"] = df["Inflation"].shift(1)
```

```

df = df.loc[2008:2024]                                # common sample, T = 17
df["COVID"] = [1.0 if y in (2020, 2021) else 0.0 for y in df.index]

specs = {
    "Model 1": ["HighTech", "HighTech_1"],
    "Model 2": ["HighTech", "HighTech_1", "Trade", "Trade_1"],
    "Model 3": ["HighTech", "HighTech_1", "Trade", "Trade_1",
               "Inflation", "Inflation_1"],
    "Model 4": ["HighTech", "HighTech_1", "Trade", "Trade_1",
               "Inflation", "Inflation_1", "COVID"],
    "Model 5": ["HighTech", "HighTech_1", "Trade", "Trade_1",
               "Inflation", "Inflation_1"],          # excl. 2020–2021
}

for name, regressors in specs.items():
    sample = df.drop(index=[2020, 2021]) if name == "Model 5" else df
    X = sm.add_constant(sample[regressors])
    res = sm.OLS(sample["GDP_growth"], X).fit(cov_type="HC3", use_t=True)
    print(f"\n{name}: N = {int(res.nobs)}, df resid = {int(res.df_resid)}, "
          f"R2 = {res.rsquared:.4f}, adj. R2 = {res.rsquared_adj:.4f}, "
          f"F = {res.fvalue:.4f} (p = {res.f_pvalue:.4f}), "
          f"DW = {durbin_watson(res.resid):.4f}")
    for v in X.columns:
        print(f"    {v:12s} {res.params[v]:9.4f} (HC3 SE {res.bse[v]:.4f})"
              f"    t = {res.tvalues[v]:6.3f}    p = {res.pvalues[v]:.4f}")

```

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