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ROBOTIC AUTOMATION IMPACTS ON ECONOMIC GROWTH: EVIDENCE FROM CHINA

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ABSTRACT

This study aims to discover the effect of robotic automation on China's economic growth. Covering the period from 1990 to 2022, this paper utilized the VAR method to investigate the case. Communications and Computer Service Imports was chosen as a variable that represents robotics. Moreover, communications and computer service exports, the Human Development Index, and patent applications were added as control variables. In addition to ensuring the stationarity of the variables, Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests are performed. Furthermore, a Granger causality test will be employed to analyze the intertemporal relationship among the variables. The evidence revealed that communications and computer service imports do have a significant effect on China's economic growth. Therefore, as computer and communication imports increase in China, it leads to an increase in the country's GDP.

Keywords: *Robotic Automation, Economic Growth, Human Development Index, Communication and Computer Service Imports, Granger causality analysis*

ROBOTİK OTOMASYONUN EKONOMİK BÜYÜME ÜZERİNDEKİ ETKİLERİ: ÇİN'DEN KANITLAR

ÖZET

Bu çalışma robotik otomasyonun, Çin'in ekonomik büyümesi üzerindeki etkisini incelemeyi amaçlamaktadır. Bu çalışmada, 1990-2022 arası döneme ait veriler VAR yöntemiyle analiz edilmiştir. İletişim ve Bilgisayar Hizmeti İthalatı, robotiği temsil eden bir değişken olarak seçilmiştir. Ayrıca,

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DOİ: 10.38120/*banusad.1826729* BANÜSAD, 2025; 8 (2), 74-88
iletişim ve bilgisayar hizmeti ihracatı, İnsan Gelişim Endeksi ve patent başvuruları kontrol değişkenleri olarak belirlendi. Değişkenlerin durağanlığını test etmek için, Augmented Dickey-Fuller (ADF) ve Phillips-Perron (PP) birim kök testleri yapılmıştır. Ayrıca, değişkenler arasındaki zamansal ilişkiyi analiz etmek için bir Granger nedensellik testi kullanılmıştır. Kanıtlar, iletişim ve bilgisayar hizmeti ithalatının Çin'in ekonomik büyümesi üzerinde önemli bir etkiye sahip olduğunu ortaya koymaktadır. Bu nedenle, Çin'de bilgisayar ve iletişim ithalatı arttıkça, ülkenin GSYİH'sinde bir artışa yol açmaktadır
Anahtar Kelimeler: *Robotik Otomasyon, Ekonomik Büyüme, İnsani Gelişme Endeksi, İletişim ve Bilgisayar Hizmeti İthalatı, Granger nedensellik analizi*

1. INTRODUCTION

The history of automation, far from new being modern invention, there is evidence of automation technologies developed in the 11th century to soften the labor of miners and in the 17th century to help labourers in various industries. In contrast, the approach of the Industrial Revolution marked a truly transformative era for automation.

The Industrial Revolution, began in 18th-century Britain and expand across Europe, witnessed a paradigm shift from human labor to machine-driven production powered by steam. This mechanization provides efficient ground for the improvement of automation technologies. Automation devices were increasingly designed to accelerate production processes, particularly for goods with rising demand. The mid-20th century experienced major advancements in transportation and communication, resulting to a rise in automobile manufacturing. D.S. Harder, an engineer with Ford Motor Company, is recognized for present the term "automation" in 1946, establishing the foundation for the modern understanding of the idea.

Industrial robots and machines that can be programmed to carry out repetitive tasks, were develop in the late 1950s and early 1960s. Created by the researchers in the U.S, the first commercially successful industrial robot, Unimate, was patented by George Devol in 1954. Originally used in the automotive industry, industrial robots have since become common in various industries, including food processing, pharmaceuticals, electronics, and metalworking. By automating repetitive and perilous tasks, industrial robots improve productivity and employee safety. Current industrial robots convey remarkable sophistication and versatility. Advancements in robotics and automation caused these machines more efficient and adaptable. Currently, industrial robots are capable to perform a various of tasks, from accurate assembly and heavy lifting to complex material handling, packaging, welding, and even functions beyond human capabilities.

China's quick economic expansion is closely connected to its pace of technological advancement. The Chinese government in March 1992, announced the "National Program for Medium and Long-Term

Sosyal Bilimler Araştırmaları Dergisi
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Scientific and Technological Development," outlining a three-decade strategy to foster technological advancement. This was followed by the "863 Plan" in 1996, which aimed to close technological divide between China and developed countries. These initiatives, along with significant fundings, have positioned China to the forefront of automation and robotics, contributing significantly to its position as the world's second-largest economy.

2. LITERATURE REVIEW

Automation, especially through robotics, has significant economic impacts by increasing productivity, stimulating innovation, and reshaping labour dynamics. Studies have highlighted that automation increases manufacturing efficiency and provides a global competitive advantage.

Prettner (2016) investigates how automation affects both economic growth and the distribution of income between labor and capital. The paper uses a theoretical model that examines the relationship between technological progress, automation, and the economy. Prettner investigates the potential effects of automation on productivity, labor market dynamics, and income inequality. He finds that automation can lead to higher economic growth by increasing productivity, but it can also lead to a decrease in the share of income going to labor. The paper argues that as automation progresses, the labor share of income is likely to decrease, which could worsen income inequality if not accompanied by policies that address these imbalances. The results highlight the need for proactive measures, such as adjustments to income distribution mechanisms or policies to manage the transition to an automated economy.

Nagano (2018) explores the impacts of digital transformation and automation in developing countries. The study, presented at the 11th International Conference on Electronic Governance Theory and Practice in Galway, Ireland, examines the trade-off between economic growth and the potential social risks associated with automation (such as job loss and increased inequality). Nagano uses a theoretical framework supported by qualitative analysis to highlight the challenges these countries face as they transition to digital economies. The paper highlights the need for careful policy planning to mitigate the risks of automation and promote sustainable, inclusive growth. The findings suggest that digital modernity has growth potential, but the associated risks must be effectively managed to prevent increasing socio-economic inequalities in developing countries.

Autor and Autor & Salomons (2018) analyze whether automation displaces labour by examining the effects of automation on employment, productivity growth, and labour share across countries and industries. The study combines macroeconomic and sectoral data, using data covering the period 1970–2016 for 28 sectors in 18 OECD countries. The methodology uses panel data regression models to assess the impact of automation-induced productivity growth on employment and labour share, controlling for technological change and structural adjustments. The findings show that automation-induced productivity growth reduces the labour share of income, but does not necessarily lead to a decline in

Sosyal Bilimler Araştırmaları Dergisi
Social Sciences Research Journal
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total employment. Instead, automation primarily displaces labour in industries but creates compensatory job opportunities in other sectors through demand-driven spillovers. This suggests that automation reallocates employment rather than displacing it entirely, but the labour share continues to decline due to increased capital intensity in production processes.

Acemoglu & Restrepo (2018) investigate the impact of technology, especially automation and new tasks, on economic growth, factor shares and employment. The study develops a theoretical model that explains how automation (the replacement of labour by machines) and the introduction of new tasks affects productivity, wages and labour demand over time. The analysis combines a conceptual framework with empirical evidence, drawing on data from the post-1970 period to understand the dynamics of technological advancement. The authors argue that while automation reduces labour demand by replacing workers with machines, the creation of new labour-intensive tasks can offset this impact by increasing labour demand and overall employment. The findings suggest that automation may lead to declines in the labour share of income and wage stagnation unless the creation of new tasks compensates for these negative trends. More importantly, technological progress has mixed effects: it increases economic growth but creates distribution challenges as gains from automation go disproportionately to owners of capital.

Antony & Klarl (2020) examine the economic availability of automation, especially when investment decisions cannot be reversed. Using a dynamic stochastic general equilibrium (DSGE) model, the study focuses on how non-return investments in automation technologies can affect long-term growth and productivity. The data period is not explicitly tied to empirical data sets but is robust to theoretical systems for analysis. The methodology includes each investment decision created by automation displacing labour and capital-intensive production quantities. The findings reveal that while automation increases short-term economic growth, the failure to feedback investment can slow down adjustments to economic shocks and potentially lead to lower long-term economic growth. The study also emphasizes that the degree of system displacement and capital rigidity play an important role in determining trade-offs between economic growth and automation.

Irmen (2021) investigates the relationship between automation, economic growth, and factor shares in the context of population aging. Using a dynamic general equilibrium model, the study analyzes the impact of automation on growth, wages, and capital returns. The results suggest that aging populations may slow growth, but automation can mitigate these effects by increasing labor productivity. However, automation shifts income towards capital, potentially exacerbating income inequality. The study emphasizes the need for policies to manage the distribution of benefits from automation.

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Innocenti & Golin (2022) analyze the relationship between perceived automation risks and human capital investment using survey data from 16 countries over the period 2012–2018. The study uses a quantitative approach combining cross-country survey responses with econometric modeling to investigate how individuals' perceptions of job automation risks affect their decisions to invest in human capital, such as training and skills acquisition. The findings suggest that employees who perceive job automation to carry higher risks are more likely to invest in training and skills development to reduce the risk of potential layoffs. However, the extent of this response varies across countries depending on labor market structures and institutional factors. The study highlights the role of policy in supporting workforce adaptability in the environment of technological change, highlighting that automation risk can be a motivator for human capital investment, especially in countries with robust education systems and reskilling opportunities.

Afonso (2024) investigates the dynamics of economic growth, automation, and labour markets in the context of Industry 4.0. Using a dynamic general equilibrium model, the study examines the impact of automation on economic performance and social equality. It finds that despite demographic challenges, automation leads to a higher skill premium and sustainable economic growth, while also increasing income inequality. The results highlight the need for policies that promote skill development to ensure equal technological benefits and reduce inequality.

Adeyeri (2024) investigates the economic impacts of artificial intelligence-driven automation in the financial services sector, in his article published in the International Journal of Scientific Research and Management (IJSRM). The study focuses on recent trends and developments over the period 2018-2023 and uses a mixed-methods approach that combines qualitative information with quantitative data analysis from case studies of financial institutions adopting AI technologies. The findings reveal that artificial intelligence-enabled automation has significantly reduced operational costs, increased efficiency, and improved service delivery in the financial services sector. However, the study also identifies challenges such as layoffs, the need for reskilling the workforce, and regulatory concerns. Despite these challenges, the overall economic impact is positive, as AI enables financial institutions to achieve higher productivity, optimize decision-making processes, and foster innovation, contributing to economic growth and competitiveness in the financial sector.

3. DATA AND METHODOLOGY

This study utilizes annual data covering the period between 1990 and 2022 in China. The annual data of Gross Domestic Product per capita growth, Communications and Computer Service Imports, Communications and Computer Service Exports were in % total and provided from the World Bank Indicator (WDI). Whereas Human Development index obtained from the United Nations Development Programme (UNDP). Patent Applications were in value total obtained from the World Intellectual

Property Organization (WIPO). All the series were converted into logarithms. The aim of this study is to explore the impact of automation on economic expansion in China. Thereby, GDP is chosen as the dependent variable.

Gross Domestic Product (GDP) is the sum of the value added by all resident producers in an economy. This calculation includes taxes added to products and deducts subsidies that are not reflected in product prices. GDP is one of the main indicators that measure a country's economic size and production capacity. (Bank, 2024). The import and export of communications and computer services covers a wide range of services. This includes international telecommunications, communication services between residents and non-residents, copyrights and licensing fees, and sharing and trading in computer data. It also includes various commercial, professional, and technical services; construction services; manufacturing services for physical inputs belonging to others; and personal, cultural, and entertainment services. In addition, other supporting services such as maintenance and repair services and public services are considered within this scope (Bank, Metadata Glossary, 2024). The Human Development Index (HDI) is a comprehensive indicator used to measure the general level of well-being in a society. The HDI focuses on three basic dimensions of human development: a long and healthy life, access to knowledge, and an adequate standard of living. The long and healthy life dimension is measured by life expectancy at birth, while access to knowledge is assessed by indicators such as average years of schooling and expected years of schooling. An adequate standard of living is calculated using gross national income per capita. This index provides a more comprehensive perspective on development by considering not only a country's economic size but also the quality of life of its individuals. The HDI is used as an important tool for comparisons between countries and serves as a guide for governments in their policy development processes. (UNDP, 2024). According to WIPO, patent applications refers to a request for the grant of a patent filed at a patent office by an applicant, which includes all relevant documents and fees required for obtaining a patent (WIPO, 2024).

Table 1 provides a comprehensive summary of the dependent and independent variables, their abbreviations, proxies, and the respective data sources for the empirical model.

Table 1: Variables

Variable	**Notation**	**Proxy**	**Database**
Gross Domestic Product (GDP)	LGDP	The annual data of Gross Domestic Product (GDP) per capita growth	WDI
Patent Applications	LPATENTS	Patent Applications were in value total	WIPO

DOİ: 10.38120/*banusad.1826729* BANÜSAD, 2025; 8 (2), 74-88

Communications and Computer Service Exports	LCCEXP	Communications and Computer Service Exports were in % total exports	WDI
Communications and Computer Service Imports,	LCCIMP	Communications and Computer Service Imports were in % total Imports	WDI
Human Development index	LHDI	Human Development index	UNDP

Source: World Bank Indicator (WDI), World Intellectual Property Organization (WIPO), United Nations Development Programme (UNDP)

In this study, the Vector Autoregressive (VAR) model and Granger causality analysis developed by Sims (1980) and Granger (1969) were used to examine the impact of automation on economic growth in China. The VAR model is a suitable method for analyzing dynamic relationships between multiple time series variables, allowing each variable to be considered both as a dependent and independent variable. Granger causality analysis allows for determining the direction and significance of causal relationships between variables (Fatima et al., 2024). A VAR model captures the linear interdependencies among multiple time series. For a k-dimensional time series yt=[y1t,y2t,…,ykt]′, the VAR(p) model is given by:

$$y_t = c + \sum_{i=1}^{p} A_i y_t + \varepsilon_t \quad (1)$$

where:

- c is a k-dimensional vector of constants (intercepts),
- A_i (i=1,…,p) are k × k coefficient matrices,
- ε_t is a k-dimensional white noise vector with $E[\varepsilon_t] = 0$, $= E[\varepsilon_t \varepsilon_t{}'] = \Sigma$, and $E[\varepsilon_t \varepsilon_s{}'] = 0$ for t ≠ s

Granger causality tests whether one time series *(x_t)* provides statistically significant information about another *(y_t)*, above and beyond the information contained in the past values of y_t alone. Unrestricted VAR Model is given by:

$$y_t = \alpha + \sum_{i=1}^{p} \beta_i y_t - i + \sum_{j=1}^{p} Y_j x_t - j + \varepsilon_t \quad (2)$$

Restricted VAR Model is given by:

$$y_t = \alpha + \sum_{i=1}^{p} \beta_i y_t - i + n_t \quad (3)$$

Hypotheses:

Null Hypothesis (H_0): $Y_j = 0$ for all j =1,…,p (no Granger causality from x_t to y_t.

Alternative Hypothesis (H_1): At least one $Y_j \neq 0$.

Sosyal Bilimler Araştırmaları Dergisi

Social Sciences Research Journal

DOİ: 10.38120/*banusad.1826729* BANÜSAD, 2025; 8 (2), 74-88

Test Statistic: The Granger causality test uses the F-statistic, it is given by:

$$F = \frac{(RSS_{restricted} - RSS_{(Unrestricted)/P})}{RSS_{(Unrestricted)/(T-k-1)}} \quad (4)$$

Where:

- RSS(restricted): Residual sum of squares of the restricted model,
- RSS(unrestricted): Residual sum of squares of the unrestricted model,
- *T*: Number of observations,
- k: Number of estimated parameters in the unrestricted model.

The F-statistic is compared to the critical value from the FFF-distribution to determine whether H0 can be rejected.

In addition, patent applications were added as control variables. First, unit root tests were employed to ensure the stationarity between the variables. Therefore, ADF and PP unit root tests were utilized using EViews 12. For the ADF and PP unit root tests, if the t-statistic is greater than the critical value and the p-value is less than 0.05, it means the series are stationary, or reject the null hypothesis (Bonsu & Muzindutsi, 2017). Nonetheless, if the t-statistic is less than the critical value and the p-value is greater than 0.05, it means the series is not stationary or cannot reject the null hypothesis. Once the data has been made stationary, select the variables for analysis and specify the lag order, which may be established using lag selection criteria such as AIC, SC, or BIC (Esen & Çelik Keçili, 2022). After deciding the lags, run the estimation. In order to check the link between the variables, a Granger causality test was employed. The aim for the test is to analyze if lagged values of one variable help to predict other variables in the model (Kamasa & Ofori-Abebrese, 2015). These are the rules of decision in granger's causality test. If the p-value is less than 0.05, variable X Granger causes Y, or variable X does help to predict variable Y. On the contrary, if the p-value exceeds 0.05, it indicates that variable X does not Granger-cause variable Y, or that there is no causality relationship that exists in the model.

4. EMPIRICAL FINDINGS

4.1. Unit Root Test

Table 2: ADF Unit Root And Stationary Test Result (With Trend And Intercept

Variables	**ADF level (with trend and intercept)**	**ADF level (with trend and intercept)**
LGDP	-3.4975 (-3.5628) *	-5.7107 (-3.5683) *

Sosyal Bilimler Araştırmaları Dergisi

Social Sciences Research Journal

DOİ: 10.38120/*banusad.1826729* BANÜSAD, 2025; 8 (2), 74-88

LPATENTS	-0.3847 (-3.5577) *	-5.3795 (-3.5628) *
LCCEXP	-4.9785 (-3.5875) *	-4.7983 (-3.5628) *
LCCIMP	-4.0947 (-3.5577) *	-6.1071 (-3.5628) *
LHDI	1.8622 (-3.5628) *	-4.8562 (-3.5628) *

Table 3: PP Unit Root And Stationary Test Result (With Trend And İntercept)

Variables	**PP level (with trend and intercept)**	**PP level (with trend and intercept)**
LGDP	-5.4335 (-3.5577) *	-10.2693 (-3.5628) *
LPATENTS	-0.3847 (-3.5577) *	-5.3767 (-3.5628) *
LCCEXP	-2.7195 (-3.5577) *	-5.1661 (-3.5628) *
LCCIMP	-3.9701 (-3.5577) *	-6.2267 (-3.5628) *
LHDI	3.2695 (-3.5577) *	-4.8151 (-3.5628) *

As explained previously, before estimating the VAR model, it is essential to conduct the unit root tests. The results for the ADF and PP unit root tests are in tables 2 and 3, respectively. For the PP test, the Barlett kernel spectral estimation technique is selected, and the Newey-West method is utilized to modify standard errors. According to the ADF test, all of the series are nonstationary at level except LCCEXP and LCCIMP. However, when the PP test was applied, only LGDP and LCCIMP were stationary at level. It means that the Ho for unit root cannot be rejected, and variables are non-stationary at level. Nonetheless, at first difference, the t statistic of all variables, for both the ADF and PP tests, exceeds the critical value (5% significance level). It implies that Ho rejected the null hypothesis, confirming that all variables are stationary at first difference.

Sosyal Bilimler Araştırmaları Dergisi

Social Sciences Research Journal

DOİ: 10.38120/*banusad.1826729* BANÜSAD, 2025; 8 (2), 74-88

4.2. VAR Lag Order Selection Criteria

Table 4: VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	153.1793	NA	3.53e-11	-9.878621	-9.645088	-9.803912
1	214.0353	97.36960*	3.32e-12*	-12.26902*	-10.86782*	-11.82077*
2	233.8835	25.14109	5.45e-12	-11.92557	-9.356708	-11.10377

In order to estimate the VAR model, it is crucial to identify the best criteria for determining the lag order. The results are displayed in Table 4 above. As Table 4 explains, the Schwarz Info Criterion (SC) was chosen for determining the optimal lag length. According to SC, the ideal lag length is one.

4.3. Granger Causality Test

Table 5 reveals the outcomes of the Granger causality test. The evidence demonstrates that there is a unidirectional relationship that exists from GDP to HDI. This suggests that fluctuations in GDP have a substantial effect on the HDI but not vice versa, meaning that changes in human development do not directly affect GDP growth. However, the economic growth may be a profound factor that influences the development in human development, which could include factors such as life expectancy, education, and income. In addition, Communications and Computer Service Imports do affect GDP, meaning that as the computer and communication imports increased in China, it will lead to a rise in the country's GDP. This indicates that imports of computer and communication technology play a generous role in driving economic growth. The imports can increase productivity through infrastructure and technology advancement. As a consequence, the increased accessibility and utilization of computing and communication technologies can encourage economic activity, stimulate competitiveness, and support long-term GDP growth.

Table 5: Granger Causality Test Result

Null hypothesis	f-statistic	P-value
GDP does not Granger - Cause Patent	0.17728	0.6769
Patent does not Granger -Cause GDP	0.63802	0.4312
HDI does not Granger -Cause GDP	0.07764	0.7826
GDP does not Granger -Cause HDI	4.60765	0.0406
CCImports does not Granger -Cause GDP	7.64313	0.0103
	0.04496	0.8336

DOİ: 10.38120/*banusad.1826729* BANÜSAD, 2025; 8 (2), 74-88

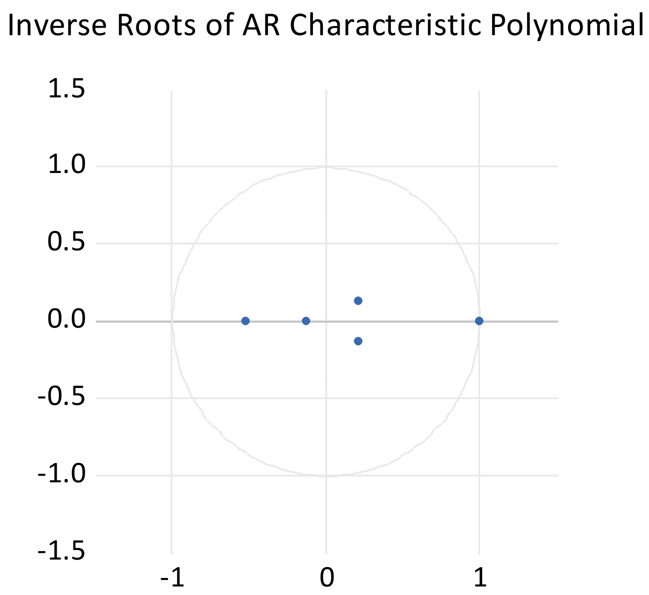
GDP does not Granger -Cause CCImports	0.77616	0.3858
CCExports does not Granger- Cause GDP	0.01191	0.9139
GDP does not Granger -Cause CCExports	2.93750	0.0976
HDI does not Granger -Cause Patent	0.02495	0.8756
Patent does not Granger -Cause HDI	0.42706	0.5188
CCImports does not Granger -Cause Patent	3.91117	0.0579
Patent does not Granger - Cause CCImports	9.63327	0.0043
CCExports does not Granger - Cause Patent	0.50068	0.4850
Patent does not Granger - Cause CCExports	5.09177	0.0320
CCImports does not Granger - Cause HDI	0.40376	0.5303
HDI does not Granger Cause - CCImports	1.69069	0.2041
CCExports does not Granger - Cause HDI	0.31490	0.5792
HDI does not Granger Cause - CCExports	0.00328	0.9547
CCExports does not Granger - Cause CCImports	0.01227	0.9126
CCImports does not Granger - Cause CCExports		

Furthermore, HDI granger cause patent applications, meaning that enhancements in human development are a leading factor of expanded patenting activity. Improvements in HDI, which reflects on increasing the quality of education, healthcare, and standards of living, may promote more innovative environment by fostering human capital development and composing conducive conditions to research and development. Moreover, there is a unidirectional relationship running from patent applications to Communications and Computer Service Imports, indicating that as patent applications increased, which showed by growth in technological innovation and research, will lead to a higher demand for imported capital goods, such as advanced computer and communication technologies. According to the table, Communications and Computer Service Exports does impact patent applications. It implies that increases in the export of technology and communication equipment can encourage innovation and the generation of intellectual property. This relationship points out the contribution of technological exports in supporting R&D activities, which then lead to a higher number of patent applications. Additionally, Communications and Computer Service Imports does granger cause HDI, signifying that the importation of technology and communication equipment indeed contributes significantly to improving human development. The adoption of advanced technology can strengthen education systems, overall infrastructure, healthcare services, which lead to better living standards.

Sosyal Bilimler Araştırmaları Dergisi
Social Sciences Research Journal
DOİ: 10.38120/*banusad.1826729* BANÜSAD, 2025; 8 (2), 74-88

4.4. Diagnostic Test

Figure 1: AR roots graph



Diagnostic tests were conducted to validate the stability of the established relationship sample period. Figure 1 showed roots graph stability test. It can be seen that all the roots of an AR characteristic polynomial are inside the unit circle and have an absolute value less than one. This indicates that the model's estimates are appropriate and consistent for dependable analysis.

Table 6: Diagnostic tests

Diagnostic Test	**Prob Chi-sq**
Normality test	0.0000
Autocorrelation test	0.1350
Heteroskedasticity test	0.1162

Normality, autocorrelation, and heteroskedasticity diagnostic tests were also carried out. Table 6 shows the result of normality test, using the Jarque-Bera test. The evidence informs that prob Joint is 0.0000. It means that the model does not follow a normal distribution, given that the p-value is below the 0.05 significance threshold. However, although the residuals were not normally distributed, since the data used is 31, then it is disregarded. Table 6 reveals the result of the autocorrelation test using the Correlogram-Q statistic. The evidence indicates that the p-value is 0.1350, which is higher than 0.05. This suggests that the model is not affected by serial correlation since the p-value for all lags exceeds the 0.05 significance threshold. In other words, the residuals are uncorrelated over time. The absence of autocorrelation suggests that the model successfully represents the dynamic interaction between the

DOİ: 10.38120/*banusad.1826729* BANÜSAD, 2025; 8 (2), 74-88

variables effectively, and there is no excluded temporal pattern that could bias the result. Table 6 shows the result of the heteroskedasticity test, conducted using the White test, revealing that the p-value is greater than the 0.05 significance level, which is 0.1162. It implies that the model is homoscedastic. To put it differently, the variation of the residuals remains consistent over time. The absence of heteroskedasticity means that the model's standard errors are reliable. It can be concluded that the model meets the stability conditions.

5. CONCLUSION

This study empirically examined the influence of automation on China's economic development using a VAR model. To achieve this, the stationarity of the series and the causal relationships among variables were tested to determine the degree of association between communications and computer service imports and economic growth. In addition, HDI, communications and computer service exports, and patent applications were included as control variables. Based on ADF and PP unit root tests, all series were found to be stationary at first difference.

The findings of the study indicate that communications and computer service imports have a significant positive effect on China's economic growth. This result is consistent with Prettner (2016), who analyzed the impact of automation on economic advancement and the distribution of income between capital and labour, concluding that automation enhances productivity and thereby stimulates growth. While Antony and Klarl (2020) reported that automation may generate short-term economic growth, our findings suggest that imports of computer and communication technologies significantly contribute to long-term growth dynamics. Increased accessibility and use of these technologies can enhance economic activity, improve competitiveness, and support sustained GDP growth.

Although our findings partially align with Irmen (2021)—who emphasized population aging as a core factor—only a limited number of studies have used communications and computer service imports as a proxy for automation. Therefore, this study contributes to the literature by offering new evidence on how automation-related technology imports foster economic development in China.

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