EVOLVING LANDSCAPE OF ARTIFICIAL INTELLIGENCE IN GEORGIA

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ABSTRACT

The current paper provides a detailed evaluation of Artificial Intelligence (AI) adoption in Georgia, identifying the opportunities and challenges within political, economic, social, technological, legal, and environmental contexts. We developed a novel theoretical framework to characterize AI stakeholders and used an Autoregressive Distributed Lag (ARDL) model to investigate how AI influences macroeconomic indicators like high-technology exports. The findings indicate significant positive short-term and long-term impacts of R&D expenditure on high-technology exports, with ICT goods exports also contributing positively over time. In contrast, real GDP negatively affects these exports, suggesting the need for policy adjustments to support AI implementation. The study highlights the importance of strengthening policy frameworks and promoting digital education to enhance AI integration in Georgia's digital strategy.

Keywords: Artificial Intelligence, Developing Economy, Georgia, ARDL

JEL Code: O33, O14, O10

1 INTRODUCTION

In the modern digital world, artificial intelligence (AI) is developing dynamically. In many businesses it is identified as a source of increasing efficiency and generating insights for better decision making.

In a highly diverse developing world, positive relationship is observed between the digital transformation index and economic development, labour productivity and job employment (Ali, 2022). According to Dahlman, Mealy, and Wermelinger (2016), "the digital economy fosters growth and productivity and supports inclusive development".

Considering the international experiences, the AI may be an important element in accelerating development and economic growth in developing countries, but its major impacts are still not fully investigated.

Our objective is to analyse the impact of AI on the example of small-scale developing economies. For this purpose, the Caucasus region and in particular Georgia was chosen.

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The purpose of this paper is to explore AI current state in Georgia and identify the factors that would influence AI future adoption in the country. Therefore, the main research question is, "What challenges is Georgia facing in adopting AI?" This study endeavors not only to outline these challenges but also to propose strategic directions for policy and implementation that could facilitate a smoother integration of AI technologies in Georgia.

2 LITERATURE REVIEW

Review of the literature indicates a scarcity of academic sources regarding the utilization of artificial intelligence in Georgia. Notably, scholarly works on this subject have only recently emerged.

Researchers have raised questions about the establishment of an AI national strategy and an appropriate strategic framework (Eristavi, D., Davituri, G. 2021). According to the PMC research paper, "having a clear strategy could help to coordinate several governmental policies and ensure that there is no contradiction between the AI strategic goals and certain sectoral goals" (Parulava, 2021).

Gigiuashvili and Makasarashvili (2021) also reviewed the potential of artificial intelligence for Georgia in their work – "possibilities of using artificial intelligence in post-pandemic Georgia". In their article, authors speak about the necessity of development of artificial intelligence technologies in Georgia. They also note that a possible risk of AI adoption can be rising unemployment.

Abuselidze and Mamaladze (2021) also raised the issue of unemployment and possibility of a reduction in labour demand. The authors recommend that the state should pay special attention to the creation and development of educational programs on artificial intelligence.

Napetvaridze (2022) in his work "Artificial intelligence in Georgia and in the world" notes that the development of digital technologies is an irreversible process. The author believes that artificial intelligence can be a source of increasing efficiency in the provision of public services and ensuring the participation of citizens in the decision-making process.

In summary, the literature review highlights a growing interest in the strategic development and implications of artificial intelligence in Georgia, yet reveals a critical lack of comprehensive research on the subject.

3 METHODOLOGY

The research begins with a literature review to identify what previous studies have reported about AI technology specifically in Georgia. We examine academic articles, corporate reports, and policy documents to spot gaps.

Following the literature review, we introduce a novel framework designed specifically for this research to describe and analyze the AI ecosystem in Georgia. This framework details the components and stakeholders within the ecosystem and explores how they interact and affect AI development.

Prior to conducting the quantitative analysis, a PESTLE analysis is performed. This analysis assesses the Political, Economic, Social, Technological, Legal, and Environmental factors that could influence the AI ecosystem in Georgia. The PESTLE analysis helps to identify external factors that might affect the development and deployment of AI technologies, thereby providing a macro-environmental backdrop against which the AI ecosystem operates.

The main quantitative analysis uses an Autoregressive Distributed Lag (ARDL) model to investigate how R&D expenditure, ICT goods exports, and real GDP influence high-technology exports. The ARDL model is suitable for our study as it can analyze both the immediate and delayed effects of these economic variables. We test the following hypotheses:

- H1: Increased R&D expenditure can boost high-technology exports in the short term.
- H2: Over the long term, a higher share of ICT goods exports significantly enhances high--technology export growth.
- H3: Real GDP negatively impacts high-technology exports in the short term, requiring careful economic policy adjustments.

The findings will not only fill existing gaps in the current research but also offer valuable insights and frameworks that can be adapted by other researchers and policymakers in similar emerging markets.

4 GEORGIAN CONTEXT

According to the “Government AI Readiness Index 2023” of Oxford Insight, Georgia ranks 99th in the global context out of 193 countries worldwide. It positions 10th out of 18 countries on a regional scale (South and Central Asia) and falls behind its neighbour countries: Turkey, Azerbaijan and Armenia (AI Readiness Index 2023).

According to the Index indicators, the country has no AI vision, maturity and lacks infrastructure. However, Georgia scored the highest in terms of Data Availability and Data Representation. The state has made significant improvements in governance, ethics, and digital Capacity. With insights gleaned from AI Readiness Index, it becomes imperative to delve further into Georgia’s artificial intelligence landscape. Consequently, we have created a novel theoretical framework to analyze the state of AI ecosystem in Georgia.

In Figure 1, we present the Georgian Artificial Intelligence Ecosystem, composed of the following groups: local and foreign investors, government, businesses, and local community. In the center of the model, we placed the business association AI Georgia. Its aim is to promote and raise awareness of artificial intelligence throughout the country. The organization also promotes the introduction of artificial intelligence into the private sector and fosters the opening and maintenance of dialogue between enterprises, government, and state legislatures (AI Georgia).

If all bodies would strengthen cooperation between each other, we would observe AI enhancement, opportunities could be maximized, and risks could eliminate. However, the limitations of this framework are that it does not account the differences in the influence and impact of stakeholders. These are complex issues and more in-depth research is required.

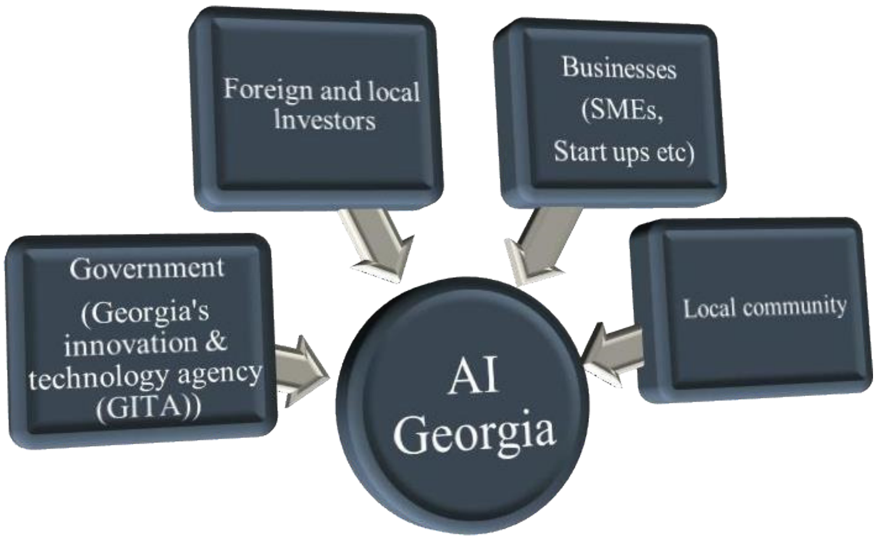

Fig. 1: A description model for assessing the AI ecosystem and its current agents in Georgia.

4.1 PESTLE Analysis addressing AI adoption in Georgia.

The aim of the PESTLE analysis of this research is to develop a deep understanding of the external environment affecting the stages of artificial intelligence development in Georgia.

Political Factors can play a crucial role in the AI adoption and development in Georgia. Georgian legislation doesn't define a concept of artificial intelligence, neither special legislation regulating artificial intelligence software services do exist (Eristavi, D., Davituri, G. 2021). We also believe that artificial intelligence should be given a special importance in Georgia's legal framework and that its application to other legislative requirements should be transparent. According to the OECD (2021), the country has undertaken efforts to develop an institutional and policy framework for digital transformation. The adoption of a comprehensive national digital strategy would help define clear objectives and measures and strengthen cooperation between stakeholders. Furthermore, the central point of AI policy implementation should be investment in R&D (OECD 2022).

Economic factors to consider are the cost of adopting AI and the costs of maintaining AI systems. As mentioned in the report of McKinsey Global Institute (2018), Initial investment, the continuous improvement of technology and applications and significant transitional costs could limit the adoption of AI by smaller companies. Unsurprisingly, the transition to AI is likely to cause number of costs for Georgian business environment since it is mostly composed of small firms. Other economic factors include the impact on employment rate, economic growth, and employee skills. These are sensitive indicators for the country.

AI adoption leads to human capital development and fosters new skills development. Wilson et al. (2017) conducted research on jobs in AI-driven businesses and technology.

They confirmed that companies that use advanced artificial intelligence systems need employees who can explain to non-technical professionals the internal workings of complex algorithms and introduced three new roles. Trainers are human workers who can teach AI systems how to operate. Explainers bridge the gap between technology and business leaders. Sustainers — will help ensure that the AI system works as designed. In Georgian AI driven business environment, we can expect the same scenarios. Higher AI adoption could lead to the development of ICT skills.

Social factors, particularly how society views and interacts with AI, are another important aspect to consider. Therefore, it is crucial to determine if any public fears exist, as cultural values and technological literacy may influence how Georgian society perceives and adopts AI. The Georgian population currently has limited exposure to artificial intelligence, and as a result, they are not well-informed about this phenomenon. It is undeniable that understanding the extent of misunderstanding among the general public regarding AI is of paramount importance. Another research question that arises here is to what extent the hopes and expectations of the Georgian people align with reality. We believe that conducting a survey of respondents can be an ideal way to explore this subject and should be carried out accordingly.

Technological factors, related to the development and use of AI, can significantly impact the success of AI projects. According to the National Statistics office, In Georgia, the ICT sector grows and the number of employees in the sector has grown as well. There were 2.86 million internet users in Georgia and internet penetration rate stood at 76.4 percent of the total population at the start of 2023 (Digital Georgia 2023). The penetration rate of the Internet in Georgia is estimated at 73.5 percent by 2026. The growth is expected in the mobile phone subscriptions and the number of fixed-broadband subscriptions per 100 inhabitants. This proves that technological environment is dynamically developing in the country and artificial intelligence development can be based on solid foundations. Moreover, the availability of data is another vital technological factor influencing AI development. Although Georgia established the Open Data Portal in 2015, challenges persist in terms of data availability (Eristavi, D., Davituri, G. 2021). The Global Data Barometer reveals that Georgia faces obstacles in open

Political	Economic	Social
• Governmental policies • Investments in AI • Grants and fundings • Impact on National Security • Impact on labor laws	• Cost of AI adoption Potential economic impact on AI • Impact on employment rate and job markets Economic barriers • Impact on skill market	• AI public perception • Positive / Negative impacts of AI solutions on society • Technological literacy of the society
Technological	**Legal**	**Environmental**
• Data availability • Technological infrastructure • Technology changes	• Local laws and regulations • Intellectual property protection for AI-related patents, copyrights etc. • Date privacy laws	• High energy consumption of AI systems • AI equipment recycling and disposal. • Sustainable development

Tab. 1 PESTLE Analysis addressing AI adoption in Georgia

data governance due to the absence of a framework for exchanging public data. However, advancements in cloud computing technologies offer promising prospects for accelerating AI development, reducing costs, and enhancing flexibility, particularly for small and medium-sized enterprises (ITU 2021).

Legal factors include local laws and regulations that can affect AI further adoption.

The most relevant legal instrument in the field of Artificial Intelligence is the Georgian Personal Data Protection Act, which sets the standards for the collection and possession of data (Parulava 2021). The Georgian National Bank has developed regulatory measures for the risk management of data-based statistical, artificial intelligence and machine learning models to encourage the appropriate use of models and reduce potential risks, aimed at establishing a framework for effective risk management. Model Risk Management Standards consider the current practices and challenges of the Georgian financial sector and modern international supervision experiences (NBG 2022). In parallel, Georgia's oversight of intellectual property rights is facilitated by the government agency Sakpatenti, with the country holding longstanding membership in both the World Intellectual Property Organization (WIPO) and the World Trade Organization (WTO).

Environmental factors can have a crucial importance. The energy consumption associated with AI compute has direct implications for production, transportation, and operations, contributing to factors such as carbon footprints and water consumption (Wynsberghe 2021). However, there is a growing acknowledgment of the need for sustainable approaches to AI development. Scholars have begun exploring the concept of "sustainable artificial intelligence," which prioritizes the compatibility of AI development with environmental conservation efforts (Yu, Zhang, et al. 2021).

Additionally, the disposal and recycling of artificial intelligence equipment present environmental challenges that need consideration, particularly as AI technology becomes more prevalent in Georgia. Ensuring responsible environmental management of electronic waste is crucial for the long-term sustainability of artificial intelligence. One potential solution could be implementing frameworks such as the Artificial Intelligence-based Hybridized Intelligent Framework (AIHIF) for automated recycling, which optimizes waste management processes (Wisskirchen et al. 2017). By addressing these environmental factors, Georgia can foster sustainable AI development while minimizing its ecological footprint.

4.2 Exploring the Economic Dynamics of AI Development

We aim to investigate the dynamics of AI development in Georgia, focusing on its technological export capabilities. Our study employs an Autoregressive Distributed Lag (ARDL) model to analyze both short-term and long-term relationships between key economic variable.

The dependent variable is high-technology exports (% of manufactured exports). Independent variables include research and development expenditure (% of GDP), ICT goods exports (% of total goods exports), and real GDP.

R&D expenditure drives innovation, while ICT goods exports reflect the digital economy's role in technological advancement. Real GDP captures the broader economic environment's influence on technological exports.

4.2.1 4.2.1 Model Specification and data preparation

The general form of the ARDL model for our study is specified as follows:

$$\mathrm{HTE}_t = \alpha_0 + \sum_{i=1}^{p} \beta_i\, \mathrm{HTE}_{t-i} + \sum_{i=0}^{q} \gamma_i\, \mathrm{RD}_{t-i} + \sum_{i=0}^{s} \lambda_i\, \mathrm{ICT}_{t-i} + \sum_{i=0}^{t} \phi_i\, \mathrm{GDP}_{t-i} + \epsilon_t \tag{1}$$

Our analysis uses data from the National Statistics Office of Georgia and the World Bank, covering the period from 2013 to 2021. We disaggregate these annually reported variables into quarterly data using the Denton-Cholette method (Sax C, et. al 2013). We perform log transformations on all variables to stabilize variance and normalize data distribution. For real GDP, we additionally adjust for seasonality using the X-11 method, removing seasonal effects to better analyze underlying trends and cyclical patterns.

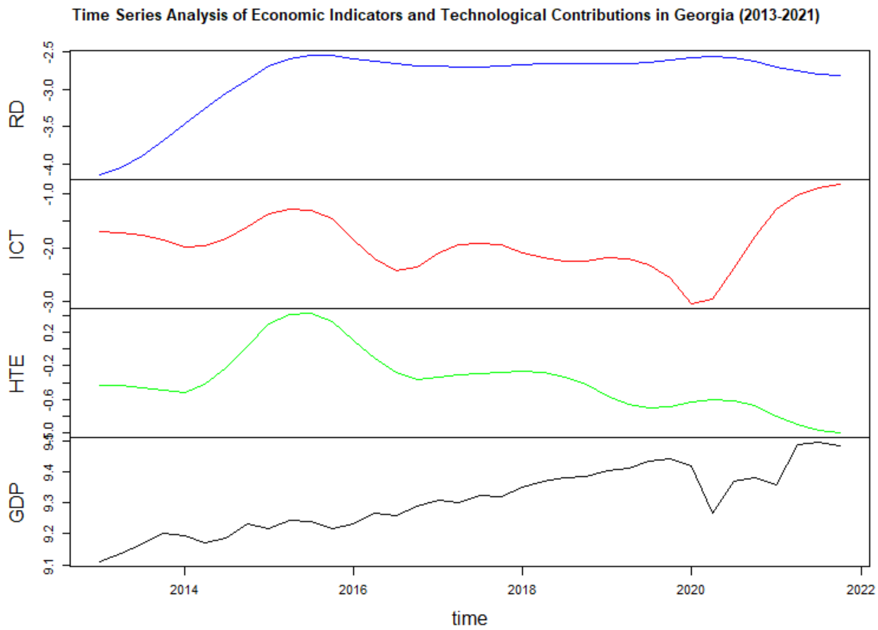

Fig. 2: Time Series Analysis of Economic Indicators and Technological Contributions in Georgia (2013-2021)

Source: Analysis conducted by the authors using R software

Based on our analysis of the time series graphs for economic indicators and technological contributions in Georgia from 2013–2021, as illustrated in Figure 2, the data exhibits non-stationary behavior overall. The variables display level shifts, trends, and lack of mean reversion, indicating that the time series are not stationary. Further tests, such as the Augmented Dickey-Fuller (ADF) test, could be employed to formally assess the stationarity of each series.

We first perform the ADF test to determine the integration order of each variable. If our variables are either I(0) or I(1), the ARDL model is appropriate. Given this, we proceed with the ARDL approach, treating all variables as I(0) for model estimation.

Level	1pct	5pct	10pct	Statistic
l.HTE.tau3	-4.15	-3.5	-3.18	-5.7215978502874
l.HTE.phi2	7.02	5.13	4.31	18.8835095224786
l.HTE.phi3	9.31	6.73	5.61	16.9827413362574
First difference				
d.l.HTE.tau3	-4.15	-3.5	-3.18	-3.99947469703212
d.l.HTE.phi2	7.02	5.13	4.31	7.99599027254634
d.l.HTE.phi3	9.31	6.73	5.61	11.3677229951813

Tab. 2 ADF Test results for HTE

Source: Analysis conducted by the authors using R software

Level	1pct	5pct	10pct	Statistic
l.RD.tau3	-4.15	-3.5	-3.18	-1.54654201198179
l.RD.phi2	7.02	5.13	4.31	1.56622449067009
l.RD.phi3	9.31	6.73	5.61	2.27086637597985
First difference				
d.l.RD.tau3	-4.15	-3.5	-3.18	-3.48547315494067
d.l.RD.phi2	7.02	5.13	4.31	4.36457208490618
d.l.RD.phi3	9.31	6.73	5.61	6.35389321107155

Tab. 3 ADF Test results for R&D

Source: Analysis conducted by the authors using R software

Level	1pct	5pct	10pct	Statistic
l.ICT.tau3	-4.15	-3.5	-3.18	1.67755429917397
l.ICT.phi2	7.02	5.13	4.31	1.67755429917397
l.ICT.phi3	9.31	6.73	5.61	2.46524873313422
First difference				
d.l.ICT.tau3	-4.15	-3.5	-3.18	-4.1725977887524
d.l.ICT.phi2	7.02	5.13	4.31	5.87290319016142
d.l.ICT.phi3	9.31	6.73	5.61	8.78550198282987

Tab. 4 ADF Test results for ICT

Source: Analysis conducted by the authors using R software

Level	1pct	5pct	10pct	Statistic
l.GDP.tau3	-4.15	-3.5	-3.18	-3.14531048765588
l.GDP.phi2	7.02	5.13	4.31	4.10584732956181
l.GDP.phi3	9.31	6.73	5.61	5.07095660316153
First Difference				
d.l.GDP.tau3	-4.15	-3.5	-3.18	-4.76590956323406
d.l.GDP.phi2	7.02	5.13	4.31	7.6552314322281
d.l.GDP.phi3	9.31	6.73	5.61	11.4794755757278

Tab. 5 ADF Test results for GDP
Source: Analysis conducted by the authors using R software

The results of the ADF test indicate the integration orders of the variables as follows:
- High-technology exports (HTE) is integrated of order 0 (I(0)).
- Research and development expenditure (RD) is integrated of order 1 (I(1)).
- ICT goods exports (ICT) is integrated of order 1 (I(1)).
- Real GDP (GDP) is integrated of order 1 (I(1)).

These results confirm that the ARDL model is suitable for our analysis, as it can handle a mix of I(0) and I(1) variables.

4.2.2 Model Identification

Before estimating the ARDL model, we transformed our variables and ensured their stationarity. We used the function in R to determine the optimal number of lags based on the Bayesian Information Criterion (BIC), which balances model fit and complexity.

Estimation of the ARDL model was performed using Ordinary Least Squares (OLS). The function results indicated that the optimal lag structure, based on the Bayesian Information Criterion (BIC), is with lags of 2 for HTE, 2 for RD, 0 for ICT, and 1 for GDP, achieving the lowest BIC value of -86.621. This model captures the necessary past information most efficiently for our analysis.

We used the Variance Inflation Factor (VIF) to detect multicollinearity, which occurs when independent variables are highly correlated, which can cause inflated standard errors, making it difficult to determine the individual effect of predictor variables and leading to unreliable statistical inference.

	VIF
L(l.HTE, 1)	49.2794
L(l.HTE, 2)	36.8579
l.RD	436.4411
L(l.RD, 1)	2121.4321
L(l.RD, 2)	789.4687
l.ICT	1.7782
l.GDP	8.2569
L(l.GDP, 1)	6.4074

Tab. 6 Multicollinearity Assessment of Economic Indicators
Source: Analysis conducted by the authors using R software

Term	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	7.70770	1.33755	5.7626	0.00001
l.RD	3.34820	0.38190	8.7672	0.00000
l.ICT	0.04004	0.01178	3.3993	0.00236
l.GDP	-0.42750	0.14367	-2.9756	0.00658

Tab. 7 Short-run Multipliers
Source: Analysis conducted by the authors using R software

The VIF results indicated potential multicollinearity issues among the variables in the ARDL model. High VIF values for lagged high-technology exports (HTE) and research and development expenditure (RD) suggest significant correlation with other variables. Lower VIF values for ICT goods exports (ICT) and real GDP (GDP) imply less multicollinearity for these variables.

We conducted diagnostic tests on our regression model's residuals. The Breusch-Godfrey test showed no significant autocorrelation ($p > 0.05$). The Breusch-Pagan test indicated constant variance of residuals, with no significant heteroscedasticity ($BP = 5.6$, df-8, $p = 0.69$). The Jarque-Bera test confirmed that the residuals follow a normal distribution ($p = 0.24$).

The validation tests confirm that our ARDL model's residuals show no significant autocorrelation, heteroscedasticity, or deviation from normality, demonstrating that key assumptions are satisfied. However, despite the model's robustness, we observed potential multicollinearity among some variables, which should be considered in parameter interpretation. These findings support the overall reliability of our model.

The regression results show a highly significant model (p-value < 2e-16) with an adjusted R-squared of 0.995, indicating an excellent fit. Most coefficients are statistically significant, suggesting strong relationships between high-technology exports and the independent variables.

Key findings include:

- Lagged high-technology exports (HTE) have a significant positive effect at lag 1 and a negative effect at lag 2.
- Research and development expenditure (RD) has a significant positive immediate effect and significant negative and positive effects at lags 1 and 2, respectively.
- ICT goods exports (ICT) and real GDP (GDP) show significant effects, with ICT positively and GDP negatively influencing high-technology exports.

These results suggest that past values of HTE, RD, and GDP significantly impact current high-technology exports, highlighting the importance of these factors in AI development in Georgia.

Term	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	39.89188	4.27595	9.3294	0.00000
l.RD	2.12219	0.27776	7.6404	0.00000
l.ICT	0.20725	0.05893	3.5170	0.00177
l.GDP	-3.66500	0.43692	-8.3883	0.00000

Tab. 8 Long-run Multipliers
Source: Analysis conducted by the authors using R software

The short-run multipliers from the regression results show the immediate impact of each independent variable on high-technology exports:

- A 1% increase in R&D expenditure boosts high-technology exports immediately by approximately 3.35% ($p < 0.00001$).
- 1% rise in ICT goods exports results in an approximate 0.04% increase in high-technology exports ($p = 0.00236$).
- A 1% increase in real GDP decreases high-technology exports by about 0.43% ($p = 0.00658$).

The long-run multipliers from the regression results show the sustained impact of each independent variable on high-technology exports:

Over the long term, a 1% increase in R&D expenditure correlates with a 2.12% rise in high-technology exports ($p < 0.00001$).

A 1% rise in ICT goods exports leads to a 0.21% increase ($p = 0.00177$).

A 1% increase leads to a long-term decrease of about 3.67% in high-technology exports ($p < 0.00001$).

The findings from our ARDL model analysis provide substantial evidence supporting the formulated hypotheses regarding the impact of R&D expenditure, ICT goods exports, and real GDP on high-technology exports in Georgia. Specifically:

- Hypothesis 1 was clearly supported, as R&D expenditure showed a significant positive impact on high-technology exports in the short term, highlighting its immediate benefits to technological export capabilities.
- Hypothesis 2 received partial support, indicating a modest yet positive effect of ICT goods exports on long-term high-technology export growth.
- Hypothesis 3 was also confirmed, with real GDP negatively affecting high-technology exports in the short term, emphasizing the necessity for strategic economic adjustments.

The robustness of the ARDL model, confirmed by diagnostic tests showing no issues with autocorrelation, heteroscedasticity, or normality deviations, lends further credibility to these results. However, the presence of multicollinearity suggests caution in the interpretation of some effects, particularly those related to overlapping economic variables.

Overall, these insights not only validate our hypotheses but also highlight the necessity for continued R&D investment and the strategic support of the digital economy. For policymakers, these findings emphasize the importance of addressing the complexities introduced by real GDP dynamics to bolster Georgia‘s position in the global high-technology market.

5 DISCUSSION AND CONCLUSIONS

This study evaluated the adoption of Artificial Intelligence (AI) in Georgia, highlighting both opportunities and challenges. We introduced a new framework for analyzing AI stakeholders and employed the Autoregressive Distributed Lag (ARDL) model to examine AI‘s impact on macroeconomic indicators like high-technology exports. Our results showed significant relationships between these exports and key economic factors including R&D expenditure, ICT goods exports, and real GDP. The ARDL analysis confirmed that R&D expenditure significantly boosted high-technology exports both in the short-term and long-term, while ICT goods exports also contributed positively over time. However, real GDP negatively impacted these exports, underscoring the need for specific economic policies to support AI adoption.

The study also stressed the importance of strengthening policy frameworks and enhancing digital education to advance AI implementation nationwide. Despite relying on publicly available data and not extensively exploring AI’s direct economic impacts or its application in specific business environments, the research provided valuable insights into Georgia‘s AI ecosystem and suggested areas for further investigation.

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