



## The Impact of Economic Intelligence on Foreign Trade, Egypt as a Model for the Period (1990 - 2020)

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### KEYWORDS

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### ABSTRACT

The paper aims to present the theoretical framework of economic intelligence and foreign trade, and to measure and analyse the relationship between economic intelligence and foreign trade in Egypt, relying on the quantitative statistical analytical approach. The research was based on the hypothesis that economic intelligence has a positive impact on foreign trade. The dependent variable is the percentage of total trade in GDP, while the explanatory variables are information and communication technologies as a percentage of GDP, spending on research and development as a percentage of GDP, Patent applications, foreign direct investment as a percentage of GDP, medium and high-tech manufacturing value added as a percentage of total value added and enrolment in higher education as a percentage of total enrolment. Among the most important results obtained, the test value (F) used (4.5505), which indicates the importance of the model, and that the economic intelligence contributes significantly to a positive impact on Egypt's foreign trade, (t) reached 0.2653916, while the coefficient of determination (R-squared) rate reached 0.8487, meaning that 0.8487 of the application in the variable is due to its explanatory value. Several proposals were also presented.

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## 1. INTRODUCTION

The foreign trade sector supports other key sectors by influencing many economic investments, and it is a key factor in a country's ability to leverage available options. As a developing country, Egypt has the potential to stimulate this formative sector to become an effective contributor to its global identity. The research problem stems from the question: Does economic intelligence, through its indicators, affect Egypt's foreign trade? The study also hypothesizes that economic intelligence has a positively affects Egypt's foreign trade. The study aims to highlight the role of smart economic indicators in the field of foreign trade. The research relied on descriptive, analytical and quantitative approach to reach several results.

### 1.1 Theoretical background:

New information about the activities of industrial organizations in the international economy contributes to the development of economic intelligence, enabling researchers and policy makers to focus on many promising initiatives that

could have a significant impact on international trade. This development can be achieved using digital trade models. [Starostina & Koshkina, 2022]. It suggests that the natural tendency for countries around the world is to implement economic intelligence strategies that can be made effective by Assessing their current status. Research indicates that designing databases for complex economies contributes to supporting economic globalization.

Over the past two decades, economic relations between countries have evolved into more complex ways of governance, enabling intelligence economics to provide multidisciplinary solutions to help countries respond to more complex scenarios. (Adami, S., 2019). The importance of intelligence economics lies in its role as an effective means of obtaining the necessary information about other competitors to advance and achieve a competitive advantage in the market. This knowledge will help companies anticipate and optimize use of the market based on various marketing tools, such as cost, product, distribution, and promotions, to compete with other companies in global markets

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(Tatic, V. 2014). The foreign trade sector is a factor in attracting capital, which contributes to the state treasury's foreign currency and promotes development in other sectors. Consequently, macroeconomic variables have a positive impact. Accordingly, some economic studies have shown that indicators of economic intelligence, including spending on education and health,

Advanced technological developments, through research and development, increased patenting, and information and communications technology, have led to increased and growing foreign trade. This focus has become more widespread in recent years, particularly since World War II, when economic prosperity began to depend more on international relations and economic strategies than on military power (Caiser, L. 2016, Jebur, N. D., 2021).

## 2. LITERATURE

### 2.1 Concept of Economic Intelligence

Economic intelligence, also known as competitive or business intelligence, involves the systematic collection, analysis, and dissemination of information about the economic environment to support informed decision-making. Within the sphere of international trade, economic intelligence plays a vital role in identifying market opportunities, assessing risks, and formulating strategies to strengthen competitiveness. Developing a robust economic intelligence strategy is essential for promoting foreign trade, and this process begins with clearly identifying key information needs, such as data on economic activity, market trends, competition, and foreign policies or regulations that may influence overseas trade. Once priorities are established, it is critical to secure reliable information sources and analyse the collected data methodically to generate valuable insights. These insights should be shared strategically with decision-makers to guide effective actions. As market dynamics continually evolve, it is necessary to refine economic intelligence strategies on an ongoing basis to maintain relevance and responsiveness. In practice, foreign trade analysis relies on gathering and interpreting diverse data sources to produce actionable insights. For example, through predictive modelling and data visualization, we analysed various datasets, reports, and publications to uncover trends in global demand, export competitiveness, and emerging market opportunities. This approach revealed several promising product categories and regions for greater market penetration, including a notable increase in demand for computer hardware, particularly across Asian markets. Our findings revealed both risks and opportunities that require carefully tailored recommendations. For example, computer hardware exports to China could increase significantly if a new trade agreement is finalized, although recent climate accords may redirect some demand toward green energy technologies. To clearly communicate these complex insights, we developed customized briefing materials and interactive dashboards. An engaging presentation for policymakers highlighted actionable strategies to capitalize on emerging opportunities while mitigating threats to sustained trade growth. By following these steps, a country can build an effective economic intelligence strategy that enhances foreign trade performance. Moreover, investing in information and communication technology (ICT) can facilitate the collection, analysis, and dissemination of information, further strengthening the impact of economic intelligence (El

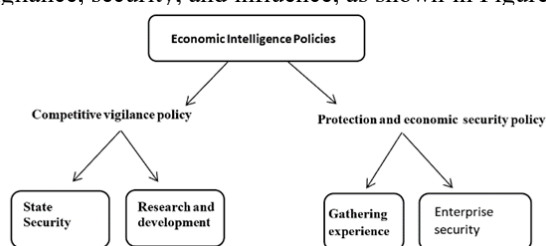
Mountassir, 2020). There are various definitions of economic intelligence. Some view it as both offensive and defensive information practices aimed at supporting an institution's strategic and tactical objectives by aligning its actions with relevant knowledge (Pokrovskaja & Golohvastov, 2016). In other words, economic intelligence can be understood as a coordinated set of activities related to researching, processing, distributing, and disseminating useful information to economic actors, conducted legally and with safeguards to protect an institution's intangible assets under optimal conditions of quality and cost (López-Robles & Cobo, 2019). It has also been defined as the process of producing knowledge that serves the economic and strategic goals of an institution, using open sources within a legal framework (Abdellaoui & Nader, 2015). Economic intelligence therefore acts as a bridge connecting multiple domains to achieve tactical and strategic aims; some scholars also define it as the process of collecting and interpreting information about the activities of current or potential competitors to identify their strengths and weaknesses (El Mountassir, 2020).

In the context of Egypt, the country's long history has been shaped by its strategic location linking Africa, Asia, and Europe, making it a commercial hub for centuries. In recent years, Egyptian leaders have worked to revitalize this role through modernization efforts that rely heavily on economic intelligence to guide foreign relations and trade policy. Teams of experts continuously monitor extensive global economic data—from specific market dynamics to broader trends—to develop a nuanced understanding of the international environment. Detailed information on customers, competitors, and policies is thoroughly analysed to inform key decisions about trade agreements and export strategies (Sharma, C., Sharma, S. K., & Gill, D., 2023). As Egypt explores new partnerships, economic intelligence plays a pivotal role in pinpointing the most promising opportunities, assessing domestic industry competitiveness, and recognizing potential barriers in foreign markets. To maximize these capabilities, the Ministry of Trade and Industry has established a dedicated Economic Intelligence unit to support data-driven decision-making and enhance Egypt's position in the global economy. Unit responsible for assembling and scrutinizing foreign trade information. In a display of dynamic collaboration, this unit works with other government agencies as well as private and academic partners (Hamza & Karim, 2025). While Egypt has established various organizations to promote exports and support businesses entering new markets, such as the Egyptian Export Promotion Centre, more can be done to bolster the economy. Information and communication technologies have been invested in to enhance financial reporting and the exchange of data between government, industry, and other stakeholders. However, online platforms and databases must be further developed and optimized if Egypt hopes to modernize successfully and increase global trade participation. The collection and analysis of economic intelligence are integral for informed decision-making and strategic development. However, to truly compete on an international level, additional focus is needed. Resources could be allocated to researching foreign demand for Egyptian goods and locating new potential partnership opportunities. Training and education might also be expanded to ensure the workforce has the skills required for global competitiveness (Moussa & Abeir, 2023). By carefully evaluating industry and market changes worldwide, smart improvements can be implemented for long-term sustainable

growth. Egypt presents an interesting case study on the impact of fiscal prudence on foreign trade from 1990 to 2020. During this period, Egypt underwent extensive economic reform and liberalization, gradually opening up the economy and leading to integration into international markets. Overall, the impact of economic intelligence in 2020 was significant. By providing insights into market opportunities and risks, economic intelligence helped drive the growth and diversification of Egypt's trade relationships. As Egypt continues to pursue economic reform and liberalization, economic intelligence is likely to remain a critical tool for enhancing competitiveness and promoting sustainable growth (Moussa & Tarek, 2023).

### 2.3 Economic Intelligence Policies

The economic intelligence system consists of three interrelated and complementary components: strategic vigilance, security, and influence, as shown in Figure 1:



**Fig. 1.** Economic Intelligence Policies

#### A. Competitive vigilance policy

This policy revolves around its adoption of research and development processes and the possibility of managing and monitoring opportunities and competition in local and foreign markets, as well as economic institutions, by ensuring that they gather experience and obtain information about the institution or general information about its environment

#### B. Protection and Economic Security Policy

There is a real interrelationship between economic security and economic competition passing the global economic change. The interrelationship between economic security and economic competition is a reality, especially after the changes taking place in the global economy. One of the importance of economic intelligence is the influencing of the surroundings and decisions (Ivan, 2013). The competitive observance and pressure refer to the offensive side in these institutions. On the other hand, the security policy represents the defensive side of any institution. The elements of economic intelligence have been identified as follows: (Othman, 2021). Ensuring the presence of effective strategic vigilance that facilitates decision-making processes in the economic field. Supporting competitiveness within economic institutions, and supporting their technological capabilities through research and development institutions to keep pace with global development in this field. Ensuring economic security within *economic* institutions and research and development institutions at the aggregate level.

### 2.4 Characteristics of Economic Intelligence:

As a result of the expansion of the knowledge economy, which is one of the main tributaries of knowledge in the theoretical, methodological, and applied fields, and the multiplicity of terms and concepts, it was necessary to clarify the most important characteristics of economic intelligence to

distinguish it from other concepts, as information constitutes its basis. It is also concerned with studying the tactical and strategic interactions at various levels and for all activities, starting with local institutions and reaching the highest decision-making centres in the country, thus affecting the international level (Köseoglu & Okumus, 2016). The most important characteristics of economic intelligence are the following:

- i. The tactical and strategic performance relies on valuable information that forms the basis for gaining a competitive advantage in the decision-making process.
- ii. It provides strong and interconnected relationships between central and local institutions, administrations, and universities through the possession and exchange of information.
- iii. It is characterized by the presence of a strong and effective administration that coordinates efforts among all economic agents, forms pressure groups, and exerts influence in its internal and external environment.
- iv. It integrates scientific, technical, economic, and legal knowledge.
- v. It is characterized by confidentiality in publishing information and in obtaining it through legitimate and legal means.

### 2.5 Stages of economic intelligence

The most important stages of economic intelligence can be reviewed as follows:

1. Determining the need for information: This is the first stage of economic intelligence activity. While it may not seem like a difficult task in most cases, it requires skill in identifying what useful information needs to be obtained. Furthermore, this stage requires the presence of specialists in the relevant field to distinguish between the vast amounts of circulated information, to sort it, and to select what is useful for subsequent analysis and dissemination (Postolea, 2021).
2. Gathering information: After determining the need for information, the second stage begins, which is to collect information that can be obtained from two sources:
3. Official sources: This refers to information that can be obtained from books, the press, various media outlets, as well as CDs.
4. Unofficial sources: These sources of information are characterized by the need for personal effort from individuals working in this field, including competitors, suppliers, and internal sources. There is also both closed and open information. Open information can be obtained from broadcasting institutions, statistical publications, printed newspapers, and commercial publications, while closed information can be obtained from reports, letters, consulates, and institutions such as embassies, which may gather confidential information without the approval of foreign governments. Such information can also be collected via satellites or through individuals from foreign nationals. Practicing economic intelligence requires protecting information using legal means and employing both human and technical resources (Anis, 2020).

5. Information processing: Information processing is one of the basic stages of economic intelligence, which depends on the value of that information for its user, as this information is acquired to analyse it appropriately and translate it to be useful and valuable information that is hidden in documents and used intelligently at the right time, and it must be noted that the problem does not lie in the scarcity of information. Rather, they are abundant, which requires sorting, evaluating, processing, and then converting them into an appropriate form and using them at the right time.
6. Broadcasting information: The dissemination of information is an essential step in the economic intelligence system to make decisions because the previous three stages of identifying, collecting, and processing information do not give the desired benefit from that information and deliver it to those in need of decision-makers, and that information has no value unless it is transmitted at the right time and in the appropriate manner. Therefore, the transmission of information should be used vigilantly and intelligently, and it should be accompanied by turning it into an act to achieve added value, as well as specialists in the field of economic intelligence, should have the ability to convince others of this process and provide techniques that help to apply it in institutions and thus contribute to achieving the goal, which is the appropriate decision-making process as it is shown in Figure 2 (Marsal-Colomer&Meléndez,2015).

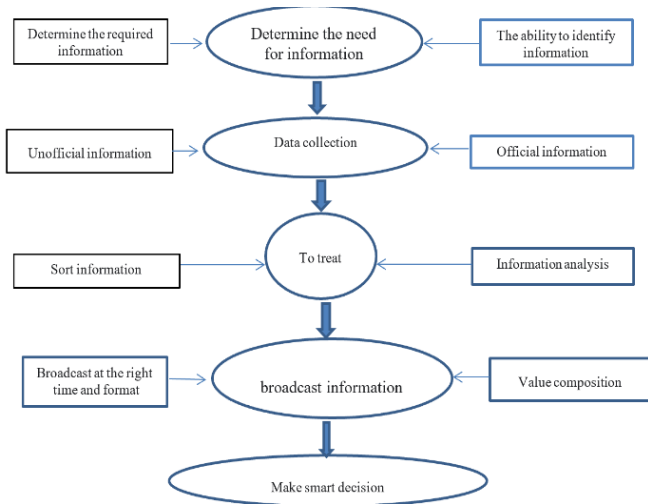


Fig. 2. Stages of economic intelligence activity.

2.6 Types of Economic Intelligence (Csurgai, 2016)

The economic literature in this field has concluded that there are three types of economic intelligence, which are as follows:

- Informational intelligence: It reflects the ability to manage information personally and individually.
- Operational intelligence: It means the ability to manage operational information in a competitive environment, and this information pertains to all episodes of the production chain, starting from the design of the product or service, through physical production, to reach the stage of quality and marketing. This type of intelligence is

considered the most adaptive to the requirements of small and medium enterprises at the local and regional levels.

- Strategic intelligence: It is related to the management of strategic information to influence the environment of the institution, and this type of intelligence finds scope for its application within the framework of major institutions, and small and medium-sized enterprises with an international orientation.

2.7 The theoretical relationship between the smart economy and foreign trade (Kofi Amanin Oduro-Kwarten et al., 2025)

Economic intelligence contributes to achieving economic growth and, in many sectors, including the foreign trade sector, through Creativity According to the economist Joseph Schumpeter, creativity is “the introduction of a new product to the market and new production methods or the creation of new forms of administrative organization for the institution” and all the processes that the institution follows by finding and applying new ideas, whatever their source, that will work to achieve economic growth.

Competitiveness: Economic intelligence is one of the messages of activity specialists in the economic field, research and development fields and monitoring the environment of the organization, as it gives the competitive advantage to institutions through their development, whether with a new product or developing an existing product and reducing costs as well as making decisions that qualify institutions to compete. Quality improvement: The British Standards Institute defined quality as one of the management philosophies of the economic institution that works to apply it to meet the needs and expectations of the customer (customer satisfaction) by obtaining a good commodity at low costs, as well as optimizing the use of human energies to achieve development and its sustainability.

3. PRACTICAL BACKGROUND

3.1 The model description stage:

At this stage, the variables included in the model are determined, and accordingly its functional form will be as follows:

$$Y = f(X1, X2, X3, X4, X5, X6) \tag{1}$$

where:

- Y: represents the dependent variable, expressed as total trade as a proportion of GDP.
- X1 Information and communications technology as a percentage of GDP
- X2: Research and development spending as a percentage of GDP
- X3: Patent registration applications
- X4: Foreign direct investment as a percentage of GDP
- X5: Medium and high-tech manufacturing value added as a percentage of total value added.
- X6: Enrolment in higher education as a proportion of total enrolment in education.

- Data collected from the World Bank website

Data were obtained from the following source: World Bank. World Development Indicators (2023).

3.2 Estimating of the Model Parameters:

At this stage, the model parameters are estimated using the Auto-regressive Distribution Lag (ARDL) model, originally applied by (Pesaran and Shin, 1999) and later developed by (Pesaran et al, 2001). The advantage of this model is that it can be applied regardless of whether the time smoothness of the variables has rank I (0) or rank I (1) or whether it is a mixture of the two, with the only condition that it does not have any smoothness. temporal order I (2); This will be determined by conducting a stationary test (unit root), and this model has better advantages in the case of short time series compared to other usual methods of cointegration testing. By taking the logarithm to the natural base of both sides of the equation, the estimate of the ARDL model according to equation (1) above will be in the

$$\begin{aligned}
 \ln(Y)_t = & \alpha_0 + \beta_1[\ln(Y)_{t-1}] \\
 & + \beta_2[\ln(X1)_{t-1}] \\
 & + \beta_3[\ln(X2)_{t-1}] \\
 & + \beta_4[\ln(X3)_{t-1}] \\
 & + \beta_5\ln(X4_{t-1}) \\
 & + \beta_6[\ln(X5)_{t-1}] \\
 & + \beta_7[\ln(X6)_{t-1}] \\
 & + \sum_{i=1}^p \gamma_1 \Delta[\ln(Y)_{t-i}] + \sum_{i=1}^p \gamma_2 \Delta[\ln(X1)_{t-i}] \\
 & + \sum_{i=1}^p \gamma_3 \Delta[\ln(X2)_{t-i}] \\
 & + \sum_{i=1}^p \gamma_4 \Delta[\ln(X3)_{t-i}] \\
 & + \sum_{i=1}^p \gamma_5 \Delta[\ln(X4)_{t-i}] \\
 & + \sum_{i=1}^p \gamma_6 \Delta\ln(X5_{t-i}) \\
 & + \sum_{i=1}^p \gamma_7 \Delta[\ln(X6)_{t-i}] \\
 & + \emptyset ECM_{t-i} + \varepsilon_t
 \end{aligned}
 \tag{2}$$

Since:

Δ: represents the change or difference of variables, t: represents time, α<sub>0</sub>: represents the constant term. p: represents the number of lags or time lags, β<sub>i</sub>: represents the long-run trends, γ<sub>i</sub>: represents the short-run trends, ECM: represents the error correction factor, ε<sub>t</sub>: represents the random variable or what is known as the random error term of the model.

3.3 Applying the model and interpreting the results:

1. Results of the Stationarity (Unit Root) Test for the Variables:

To check the stationarity of the variables, the Phillips-Perron (PP) test was used, as it is considered one of the most reliable methods for testing stationarity and determining the degree of integration of time series variables. Additionally, the Akaike Information Criterion (AIC) was employed to ensure that there is no autocorrelation problem in the random error term. This test examines the null hypothesis that the time series

has a unit root against the alternative hypothesis that it does not (Al-Bajari and Al-Mashhadani, 2019, p. 174).

It can be seen from Table 1 that all the study variables are non-stationary at their level form, indicating acceptance of the null hypothesis that the data have a unit root—in other words, they are non-stationary at level. This conclusion is based on the fact that the calculated t-values are lower than the critical t-values at the 5% significance level. However, when the first difference of these variables is taken, they become stationary and are thus considered integrated of order one, I (1).

**Table 1.** Results of the stationary test (unit root) for the model variables

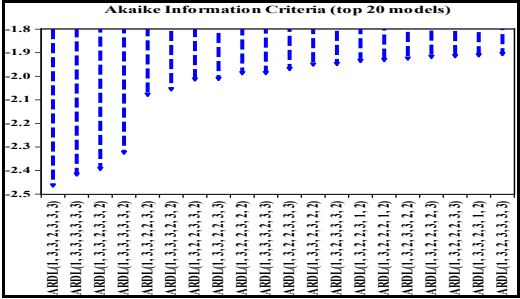
| Variables | Philips Perron Test (PP) |                     |                     |                     |
|-----------|--------------------------|---------------------|---------------------|---------------------|
|           | At Level                 |                     | At First Difference |                     |
|           | Intercept                | Trend and Intercept | Intercept           | Trend and Intercept |
| LnY       | -2.0070                  | -2.1352             | -5.3583             | -5.2790             |
| Prob.     | (0.2824)n.s              | (0.5064)n.s         | (0.0001)***         | (0.0010)***         |
| LnX1      | -1.1440                  | -3.8912             | -14.5858            | -14.1367            |
| Prob.     | (0.6848)n.s              | (0.0251)**          | (0.0000)***         | (0.0000)***         |
| LnX2      | -1.9345                  | -2.6778             | -7.8396             | -8.9762             |
| Prob.     | (0.3128)n.s              | (0.2520)n.s         | (0.0000)***         | (0.0000)***         |
| LnX3      | -0.9077                  | -2.4189             | -6.4537             | -6.3229             |
| Prob.     | (0.7718)n.s              | (0.3631)n.s         | (0.0000)***         | (0.0001)***         |
| LnX4      | -2.7080                  | -2.9455             | -6.3621             | -6.2571             |
| Prob.     | (0.0844)*                | (0.1634)n.s         | (0.0000)***         | (0.0001)***         |
| LnX5      | -1.5893                  | -1.8198             | -5.5930             | -5.5178             |
| Prob.     | (0.4755)n.s              | (0.6699)n.s         | (0.0001)***         | (0.0006)***         |
| LnX6      | -1.1029                  | -1.5563             | -4.6627             | -4.7820             |
| Prob.     | (0.7014)n.s              | (0.7862)n.s         | (0.0009)***         | (0.0033)***         |

Notes:  
 a: (\*)Significant at the 10%; (\*\*)Significant at the 5%; (\*\*\*) Significant at the 1% and (nm.'s) Not Significant.

Source: Prepared by the researcher based on the EViews 12 program

2. Determining the Optimal Lag Length:

The optimal lag lengths were determined based on the Akaike Information Criterion (AIC). Accordingly, the chosen model is (1, 3, 3, 2, 3, 3, 3), as this lag structure yields the lowest AIC value among the alternatives. Figure (3) below illustrates the selection based on the AIC criterion.



**Fig. 3.** Results of the model lag periods

Source: Prepared by the researcher based on the EViews 12 program

3. The Bound Test Approach to Cointegration:

The bound's testing methodology was proposed by Pesaran et al. (2001) to verify the presence or absence of cointegration between variables, that is, to confirm the existence of a long-term equilibrium relationship among the model variables. This is done by comparing the calculated F-statistic with the critical F-values at a 5% significance level (Al-Bajari and Al-Mashhadani, 2019, pp. 175–176). Table 2 shows the results of the bounds test for the model. It can be observed that the calculated F-statistic is 4.551, which is greater than the tabulated F-values at the 5% level for both the lower and upper bounds. This indicates the presence of cointegration, meaning there is a long-term relationship among the study variables.

**Table 2.** Co-integration test using bounds testing methodology

| Method: ARDL (1, 3, 3, 2, 3, 3, 3) |             |                      |             |             |
|------------------------------------|-------------|----------------------|-------------|-------------|
| Long Run Coefficients              |             |                      |             |             |
| Variables                          | Coefficient | Std. Error           | t-Statistic | Prob.       |
| LnX1                               | 1.077279    | 0.405921             | 2.653916    | (0.0567)*   |
| LnX2                               | -0.923957   | 0.305105             | -3.028329   | (0.0388)**  |
| LnX3                               | 1.834176    | 0.364743             | 5.028681    | (0.0073)*** |
| LnX4                               | 0.307351    | 0.071479             | 4.299861    | (0.0126)**  |
| LnX5                               | -2.259879   | 0.689358             | -3.278239   | (0.0306)**  |
| LnX6                               | -1.390220   | 0.548618             | -2.534038   | (0.0644)*   |
| Short Run Coefficients             |             |                      |             |             |
| Variables                          | Coefficient | Std. Error           | t-Statistic | Prob.       |
| ECM (-1)*                          | -0.806022   | 0.090323             | -8.923809   | (0.0009)*** |
| D(LnX1)                            | -0.318187   | 0.062703             | -5.074531   | (0.0071)*** |
| D(LnX1(-1))                        | -0.808812   | 0.105756             | -7.647872   | (0.0016)*** |
| D(LnX1(-2))                        | -0.578366   | 0.086145             | -6.713858   | (0.0026)*** |
| D(LnX2)                            | -0.559428   | 0.059826             | -9.350927   | (0.0007)*** |
| D(LnX2(-1))                        | 0.398072    | 0.056098             | 7.096052    | (0.0021)*** |
| D(LnX2(-2))                        | 0.356997    | 0.088483             | 4.034621    | (0.0157)**  |
| D(LnX3)                            | -1.138061   | 0.145401             | -7.827063   | (0.0014)*** |
| D(LnX3(-1))                        | -1.773744   | 0.262991             | -6.744498   | (0.0025)*** |
| D(LnX4)                            | 0.256866    | 0.023746             | 10.81727    | (0.0004)*** |
| D(LnX4(-1))                        | 0.062991    | 0.018277             | 3.446414    | (0.0261)**  |
| D(LnX4(-2))                        | -0.070489   | 0.016772             | -4.202873   | (0.0137)**  |
| D(LnX5)                            | -1.407383   | 0.220505             | -6.382557   | (0.0031)*** |
| D(LnX5(-1))                        | 0.612736    | 0.124486             | 4.922112    | (0.0079)*** |
| D(LnX5(-2))                        | 0.609873    | 0.140270             | 4.347859    | (0.0122)**  |
| D(LnX6)                            | -1.058391   | 0.258158             | -4.099785   | (0.0149)**  |
| D(LnX6(-1))                        | -1.229052   | 0.239644             | -5.128649   | (0.0068)*** |
| D(LnX6(-2))                        | 0.445232    | 0.178595             | 2.492967    | (0.0673)*   |
| R2 = 0.9776                        |             | Adjusted R2 = 0.8487 |             |             |

Notes:

a: (\*) Significant at the 10%; (\*\*) Significant at the 5%; (\*\*\*) Significant at the 1% and (n.s) Not Significant.

**Source:** Prepared by the researcher based on the EVIEWS 12 program

4. Estimation and interpretation of long-term and short-term results and error correction parameter:

**Table 3.** ARDL Model Results

| Bound Test Approach   |                  |                  |
|-----------------------|------------------|------------------|
| Test Statistic        | Value            | K                |
| F-Statistic           | 4.5505           | 6                |
| Critical Value Bounds |                  |                  |
| Significance          | Lower Bound I(0) | Upper Bound I(1) |
| 10%                   | 1.75             | 2.87             |
| 5%                    | 2.04             | 3.24             |
| 2.50%                 | 2.32             | 3.59             |
| 1%                    | 2.66             | 4.05             |

**Source:** Prepared by the researcher based on the EVIEWS 12 program.

Table 3 presented the results of estimating both the long- and short-term relationship, as well as the error correction coefficient. The following point can be observed:

1. Results of the Long-Term Relationship

These results were mixed and can be interpreted as follows:

- Information and communications technology has a positive and significant impact on total trade. This indicates that a 1% increase in the use of digital information technology would lead to a 1.077% increase in total trade, which aligns with economic theory.
- Spending on research and development has a negative and significant impact on total trade. This means that a 1% increase in R&D expenditure would reduce total trade by 0.924%. This could be due to the possibility that funds allocated for research and development may be misused or diverted to areas prone to administrative and financial corruption.
- Patent registration applications have a positive and significant impact on total trade. A 1% increase in patent applications would lead to a 1.834% increase in total trade, which is consistent with economic theory.
- Foreign direct investment has a positive and significant impact on total trade. A 1% increase in foreign direct investment would result in a 0.307% increase in total trade, consistent with economic theory.
- The value added from medium and high-tech manufacturing has a negative and significant impact on total trade. A 1% increase in value added from these industries would reduce total trade by 2.259%. This could be attributed to the lower quality and higher costs of Egyptian industrial products compared to foreign alternatives, which limits their competitiveness in global markets.

- Enrollment in higher education has a negative and significant impact on total trade. A 1% increase in higher education enrollment would reduce total trade by 1.390%. This might be due to an overemphasis on academic disciplines at the expense of practical and technical skills needed in the labor market

2. Results of the Short-Run Relationship and the Error Correction Parameter

- The results showed that the estimated error correction coefficient is -0.806022, which is negative, statistically significant, and less than -1 in absolute value. This confirms the validity of the adjustment mechanism over the long term, indicating that approximately 81% of any disequilibrium in the estimated model for Egypt is corrected within about one year and two months ( $1/0.806022 = 1.24 \approx 1.2$ ).
- Information and communications technology (ICT) has a significant and negative impact on total trade. This suggests that a 1% increase in ICT usage leads to a 0.318% decrease in total trade. This may be attributed to the weak digital infrastructure and a lack of widespread digital literacy.
- Spending on research and development has a positive and significant effect on total trade in the short run. A 1% increase in R&D spending results in a 0.398% increase in total trade, which aligns with economic theory.
- Patent applications have a significant and negative impact on total trade. A 1% increase in patent applications would lead to a 1.138% decrease in total trade. This may be because patent holders, especially foreign companies, are reluctant to transfer technology to the Egyptian market due to underdeveloped local industries and weak global competitiveness. Alternatively, intellectual property laws may be enforced too strictly without consideration for local market conditions.
- Foreign direct investment has a positive and significant impact on total trade. A 1% increase in foreign direct investment leads to a 0.257% increase in total trade, which is consistent with economic theory.
- Medium and high-value-added manufacturing industries have a positive and significant impact on total trade in the short run. A 1% increase in value added by these industries results in a 0.613% increase in total trade, in line with economic theory.
- Enrolment in higher education has a significant and positive effect on total trade in the second cycle. A 1% increase in higher education enrolment leads to a 0.445% increase in total trade, which also aligns with economic expectations.
- Finally, the coefficient of determination ( $R^2$ ) is 98%, indicating that 98% of the variation in total trade is explained by the explanatory variables in the model, while the remaining 2% is due to other factors or random error.

**Table 4.** Summary of ARDL Model Results

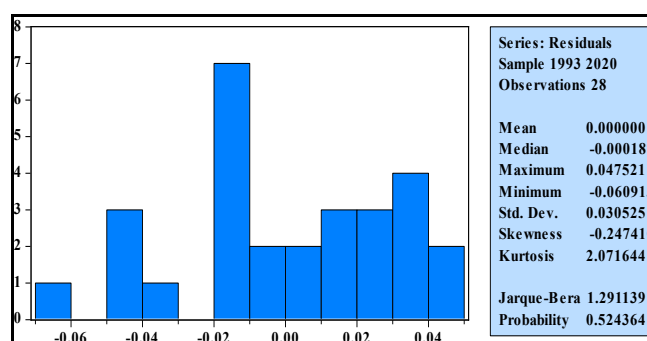
| Explanatory variables                                | Contacts with the new variable in the long term | Its relationship to the dependent variable in the short run |
|--|---|---|
| Information and Communications Technology            | The relationship is positive                    | The relationship is negative                                |
| Spending on research and development                 | The relationship is negative                    | The relationship is positive                                |
| Patent applications                                  | The relationship is positive                    | The relationship is negative                                |
| Foreign direct investment                            | The relationship is positive                    | The relationship is positive                                |
| Medium and high-value-added manufacturing industries | The relationship is negative                    | The relationship is positive                                |
| Enrollment in higher education                       | The relationship is negative                    | The relationship is positive                                |

3.4 The stage of diagnostic testing of the model and testing its stability:

After completing the estimation of the model parameters, a set of tests was conducted as follows:

1. Model performance quality tests:
2. To ensure the performance quality of the estimated model before adopting it, a series of diagnostic tests was conducted, including the following:
  - a. Testing the normality of the residuals generated by the estimated model:

It is clear from Figure (4) below that the statistical value of the Jarque-Bera test is 1.291 at a significance level greater than 5%, which means that we accept the null hypothesis indicating that the residuals generated by the estimated model follow a normal distribution, with a mean equal to zero and a standard deviation of 0.031.



**Fig. 4.** Testing the normal distribution of random errors for the model

Source: Prepared by the researcher based on Eviews 12 software outputs.

- Testing for the problem of autocorrelation in the residual values:

It is clear from Table 4 below that the statistical value of the Breusch-Pagan test is 2.275, at a significance level greater than 5%. Therefore, we accept the null hypothesis, which

indicates that the estimated model is free from the problem of autocorrelation in the residuals.

**Table 5.** Testing the problem of autocorrelation between the residuals of the model

| Serial Correlation LM Test: Breusch-Godfrey |          |                     |             |
|---|----------|---------------------|-------------|
| F-statistic                                 | 2.274720 | Prob. F(3,1)        | (0.4453)n.s |
| Obs*R-squared                               | 24.42134 | Prob. Chi-Square(3) | 0.0000      |

Notes:

a: (n.s) Not Significant.

Source: Prepared by the researcher based on EViews 12 software outputs.

- Testing whether the estimated model is free from the problem of heteroscedasticity in the residual values:

It is clear from Table 5 below that the statistical value of the ARCH test is 0.624, at a significance level greater than 5%. Therefore, we accept the null hypothesis, which indicates that the estimated model does not suffer from the problem of heteroscedasticity.

**Table 6.** Testing the problem of non-stationarity of variance of the model

| Heteroskedasticity Test: ARCH |          |                     |             |
|-------------------------------|----------|---------------------|-------------|
| F-statistic                   | 0.624101 | Prob. F(3,21)       | (0.6073)n.s |
| Obs*R-squared                 | 2.046474 | Prob. Chi-Square(3) | 0.5628      |

Notes:

a: (n.s) Not Significant.

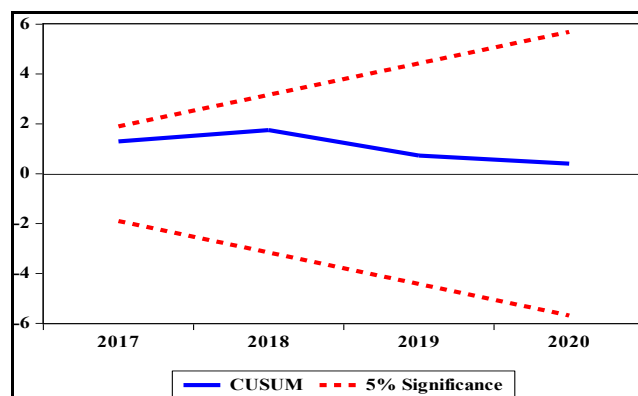
Source: Prepared by the researcher based on EViews 12 software outputs.

### 2- Structural Stability Test of Model Parameters:

After estimating the error correction form for the ARDL model, it is necessary to conduct a structural stability test for the short-term and long-term parameters of the unemployment model to ensure that the data used in the study are free from any structural changes. This test also helps to determine the extent of stability and consistency of the long-term parameters with the short-term parameters. One of the following two tests can be used:

- Cumulative Sum of Recursive Residuals (CUSUM)
- Cumulative Sum of Squares of Recursive Residuals (CUSUM SQ)

The estimated parameters of the error correction form of the ARDL model are considered structurally stable if the plot of the CUSUM SQ test stays within the critical limits (between the upper and lower bounds) at a 5% significance level. However, the parameters are not considered structurally stable if the plot of the test falls outside the critical limits at a 5% significance level as it is shown in Figure 5 (Al-Bajari and Al-Mashhadani, 2019, pp. 178–179).



**Fig. 5.** Structural stability test of the model

Source: Prepared by the researcher based on the EViews 12 program.

It is noted from Figure (3-3) above that the graph line for the Cumulative Sum of Residuals (CUSUM) test fell within the critical limits (the upper and lower bounds) at a significance level of 5%. This indicates that the estimated parameters of the error correction model used are structurally stable over the time period under study. Therefore, based on these two tests, it can be inferred that there is stability and consistency in the model between the short-term and long-term results. The study concluded that economic intelligence, through its indicators, affects Egypt's foreign trade and its development. It is suggested that future research should take into account forecasting smart economy indicators and their impact on Egyptian trade up to the year 2030.

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