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DIGITAL IMPERATIVE AND INNOVATIONS IN INTERNATIONAL TRADE

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The article analyzes the transformation of the country's foreign trade as a manifestation of the digital imperative. It examines the impact of digitalization and innovation on the structure of goods and services exports. Based on a correlation analysis, 15 global digital indices were compared, substantiating the choice of the Global Innovation Index for further calculations. Based on indicators of digitalization, macroeconomics and foreign trade, a cluster analysis was performed using self-organizing maps to determine the positions of countries in the global economy during 2011–2023, as well as their common characteristics. In particular, clustering allowed to identify a group of countries similar to Ukraine in the set of selected characteristics. This made it possible to create a database for constructing models to forecast export dynamics of the countries of this cluster, including Ukraine. The findings suggest that digital and macroeconomic factors jointly influence the structure of international trade. However, traditional regression models only partially explain the dynamics of foreign trade indicators (the share of goods exports and the share of services exports), reflecting their limited ability to capture nonlinear interactions between digital and macroeconomic variables. In contrast, neural network models demonstrate higher predictive accuracy and reveal more complex relationships between innovation, digitalization, and trade structure, underscoring the advantages of machine-learning approaches for analyzing modern trade systems.

Keywords: *international trade, digitalization, innovation, Global Innovation Index, digital economy, cluster analysis, neural network*

JEL Classification: C45, F14, F17, O33, O57

Introduction

In the current context of global economic transformation, digitalization and innovation have become key drivers of national competitiveness. International experience shows that countries actively adopting digital technologies and investing in innovations significantly expand their opportunities in international trade, particularly in high-tech manufacturing and service sector. For Ukraine, these processes are especially relevant against the backdrop of structural economic reforms, the need for post-war recovery, and the aspiration for deeper integration into global markets.

In the era of digital transformation, not only the quantitative dynamics of foreign trade but also its qualitative dimension becomes increasingly important, specifically the growing share of services, digital products, and intellectual labor in exports. Despite the full-scale war, the Ukrainian IT sector demonstrates relative resilience and continues to generate stable export revenues. At the same time, there is a decline in Ukraine's position in the Global Innovation Index, macroeconomic instability and limited public support for the R&D sector, which creates additional challenges for innovation-driven growth.

In this context, a comprehensive study of the factors shaping the dynamics of services exports, especially digital and technological ones, is essential, along with the development of effective policies to support the country's innovative and foreign trade potential. The relevance of this topic is driven by the urgent need to formulate strategic approaches for strengthening Ukraine's position in international trade through digitalization, export diversification, and the stimulation of innovative business.

Literature review

The rapid digitalization of the global economy has significantly transformed international trade, giving rise to a distinct domain – digital trade. Recent studies highlight its multifaceted nature, as economic, institutional, and technological factors simultaneously determine outcomes in this sphere. As noted by Jiang et al. (2023), digital trade has not only reshaped approaches to globalization but also deepened and expanded international trade relations, becoming a key driver of global economic growth and recovery. In this context, digital services trade occupies a particularly important place. According to Zhang and Wang (2022), it can be defined as the exchange of digital products and services conducted through cross-border data flows via information and communication networks. Its key feature lies in the use of knowledge and information in digital form as the core content, as well as the ability to conduct and complete transactions through modern information technologies.

A number of studies emphasize the economic effects of digitalization. In particular, Benz et al. (2022) demonstrate that over the past two decades, the development of ICT and the growth of air transport have reduced trade costs in services by nearly half. Shlapak et al. (2023) further note that digital transformation enhances global value chain integration and drives technological and investment priorities. This underscores the need for coordinated government measures aimed at strengthening national competitiveness in the global marketplace. Building on this argument, Zheng and Sun (2023) stress the necessity of comprehensive public strategies tailored to varying levels of digital dependency among partner countries in order to enhance export potential in digital trade. In their study, Tananaiko et al. (2023), taking into account the existing asymmetries, also emphasize the important role of international economic organizations in establishing standards for cross-border trade and ensuring compliance with universal rules.

The technological foundation of the digital economy is also a crucial determinant. Wajda-Lichy et al. (2022) showed that both traditional and broadband digital connectivity exert a positive impact on services exports, with broadband access showing a somewhat stronger effect in developed economies. Research by Antoniuk et al. (2021) further emphasizes that digital transformation reshapes national economic models, with ICT playing a pivotal role in the development of human capital and in building the skills necessary for future competitiveness. Hao et al. (2023) show that regulatory barriers hamper economic growth and call for targeted reforms to increase the openness of digital markets.

Previous studies demonstrate a broad spectrum of inquiry into the digitalization of international trade. However, considerable attention should also be paid to the econometric analysis of dynamics and interrelations between digital factors and economic outcomes. In this regard, Mulenga and Mayondi (2022) applied panel VAR models and fixed effects to assess the impact of digital services on GDP across different country groups, which enabled them to draw conclusions about long-term relationships while accounting for spatial differentiation.

Özsoy et al. (2022) examines the technological intensity of exports through the ICT Development Index (IDI), but focuses solely on high-tech exports. Wang (2024) provides a more comprehensive analysis of the impact of the digital economy on import and export flows, considering technological, social, and institutional dimensions, and employing mediation analysis, threshold effects, and clustering (K-means). This approach reveals underlying mechanisms of influence, though the findings remain limited to the specificity of the Chinese regional context.

Contemporary research increasingly employs clustering approaches to uncover hidden patterns within complex datasets. For instance, Lukianenko et al. (2023) emphasize that the use of Self-Organizing Maps (SOM) offers substantial advantages compared to other methods such as K-means, K-medoids, Principal Component Analysis, Spectral Clustering, the Dendrogram Method, the Dendrite Method, DBSCAN, OPTICS, UMAP, etc. SOM not only facilitates the formation of relatively homogeneous groups of countries based on multiple indicators but also provides a visual interpretation of the development level of key characteristics in cross-country comparisons. Therefore, the application of SOM is particularly valuable in studying the digital transformation of international trade, where the multidimensionality and complexity of factors – from levels of innovation and digital infrastructure to service accessibility and regulatory barriers – complicate the construction of a universal composite indicator.

The studies cited above demonstrate considerable methodological potential, but overall remain fragmented or excessively context-specific. Thus, while existing research contributes significantly to understanding the processes of trade digitalization, it often suffers from fragmentation, contextual limitations, or methodological constraints. This underscores the necessity of a comprehensive approach that integrates index-based analysis, clustering, and forecasting. Such an approach forms the methodological foundation of this study.

Given the gaps in existing research and the urgent need to study the impact of digitalization and innovation on the transformation of international trade, there is a need to identify key digital and economic factors shaping the dynamics of exports of goods and services, and to build forecasting models to assess future development in the context of the digital imperative.

Achieving this aim necessitates solving the following research tasks:

1. Compare global indices that reflect the level of digital transformation and select the most relevant among them.
2. Conduct a correlation and regression analysis of the relationships between digital and economic indicators.
3. Perform country clustering based on the level of digital maturity in dynamics over the period of accelerated development of digital technologies.
4. Build regression and neural network models to forecast the export of goods and services using data from countries in the same cluster as Ukraine.
5. Conduct an experimental study of the effectiveness of the forecast models, assess the impact of digital factors on the export of goods and services, and determine directions for model improvement.

Methodology

The research methodology is based on a comprehensive approach to examining the factors shaping international trade in the context of the digital transformation of the economy. The methodological framework combines both quantitative and qualitative methods, which makes it possible not only to assess statistical relationships between variables but also to interpret them within a broader economic context. Since there is no universal indicator that fully reflects the level of a country's digital integration into international trade, the study applies an indirect evaluation approach using a set of relevant international indices.

At the preparatory stage, a wide range of digitalization indices is considered (including the Global Innovation Index, ICT Development Index, among others). The key task is to identify, based on literature review and preliminary correlation testing, those indicators that most adequately reflect a country's digital maturity in the context of trade. The final choice of the baseline indicator will be substantiated after this stage of analysis.

For subsequent analysis – particularly for grouping countries, detecting hidden patterns within complex datasets, overcoming the limitation of observations, and enhancing the robustness of conclusions – the use of clustering approaches is deemed appropriate. As the methodological tool, Self-Organizing Maps are applied, since this technique, unlike many other clustering algorithms, allows not only to group objects, but also to interpret their relative position on the map both in comparison with other countries and with their previous positions across the studied period, including year-by-year analysis (Ivashchenko & Matviychuk, 2023; Matviychuk et al., 2024). A distinctive feature of SOM is that the spatial position of an object directly signals the level of its competitive standing: countries with the best and worst values of the analyzed characteristic (for example, the level of digital maturity or the intensity of international trade) according to a set of selected indicators are located in opposite corners of the map. Such a tool is indispensable in the case of unsupervised learning tasks (in the absence of a specific outcome variable), makes it possible to identify nonlinear relationships that remain invisible in classical econometric models, distinguish between leading and lagging countries, as well as capture intermediate positions and track dynamic changes for each country.

Within the identified clusters, and in line with the stated objectives, predictive models will be constructed to assess the impact of factors related to digitalization and the main determinants of countries' competitiveness on export performance. The dependent variable is defined as the Share of goods exports (Y_g) or the Share of services exports (Y_s) in total foreign trade turnover, calculated using the following formulas:

$$Y_g = \frac{E_{goods}}{E_{goods} + I_{goods}} \times 100\%, \tag{1}$$

$$Y_s = \frac{E_{services}}{E_{services} + I_{services}} \times 100\%, \tag{2}$$

where E_{goods}, I_{goods} are the exports and imports of the country's goods, and $E_{services}, I_{services}$ are the exports and imports of services.

The first indicator makes it possible to assess the share of exports in foreign trade turnover in goods. If its value exceeds 50%, this indicates that the country exports more goods than it imports, reflecting a positive balance in merchandise trade. Conversely, if the value is below 50%, imports dominate, meaning the country purchases more goods abroad than it sells. A similar approach applies to the services sector: a high indicator shows that the country is a net exporter of services (e.g., in IT, transportation, education, or tourism), whereas a low value indicates the dominance of imports and greater dependence on external suppliers.

The practical significance of these indicators lies in the possibility of comparing sectors to determine where the country is more competitive on the international markets, as well as in assessing economic specialization. In particular, a high share of services exports may indicate a digital or innovation-oriented economy. Furthermore, such calculations help to quickly determine the presence of deficits or surpluses in trade in goods and services separately and are used in international comparisons for clustering countries according to their participation model in global trade. These indicators enable a comprehensive and detailed analysis of the impact of individual factors on trade development, the formation of international competitiveness, and the determination of a country's trade orientation.

The precise model specification will be defined after a detailed examination of the collected dataset. In terms of the time dimension, the study aims to cover a sufficiently long period (at least 10 years) to identify stable patterns and dynamic changes. At the same time, it is recognized that most digitalization indicators have only begun to be systematically collected in recent years, which will determine the final temporal boundaries of the analysis.

The qualitative component of the methodology involves the analysis of international reports (e.g., the Global Innovation Index, World Bank publications), national digitalization strategies, and official statistics from statistical agencies, ministries of digital transformation and relevant government institutions. These sources are intended to provide additional insights into the dynamics of IT services exports, innovation activity, and structural changes in national economies.

Formation of the database and selection of digital development indicators

Digitalization has become a key factor in achieving economic resilience and shaping competitive advantages in the global environment. Countries that actively develop digital infrastructure and integrate digital solutions into their economies demonstrate greater stability in trade flows, even amid global crises. In contrast, states with limited access to digital technologies and institutions remain in the less developed clusters of the global economy. This exacerbates the issue of digital inequality, which constrains their capacity for sustainable development and hinders integration into the international trade system.

The rapid deployment of artificial intelligence technologies, 5G connectivity, cloud platforms, and "green" digital solutions has become a catalyst for the Fourth Industrial Revolution, significantly transforming the architecture of the global economy. In this context, countries face new challenges: how to assess the effectiveness of investments in digital infrastructure, how to measure the readiness of national technology ecosystems to adopt innovations, and which ICT indicators most accurately reflect progress in digital transformation. These questions highlight the need for a comprehensive and strategic approach that goes beyond financing and includes clear evaluation metrics.

Table 1 presents a comparison of key international indices that reflect various aspects of digitalization. These indices allow for benchmarking countries' levels of digital maturity, creating a comparative basis for analysis, and assessing the effectiveness of digital strategies in a global context.

Among the indices listed in Table 1, the Global Digitalization Index (GDI) is the most suitable for assessing the level of digitalization in different countries, which also follows from its name. Developed by Huawei in 2024, this indicator provides a quantitative measure of the progress of digital transformation at the national level. It captures multiple dimensions of digital development and allows for cross-country comparison of digital readiness and performance.

Global Digitalization Index 2024 report (Huawei, 2024) identifies four key pillars of the intelligent world: Ubiquitous Connectivity, Digital Foundation, Green Energy, and Policy & Ecosystem. The 2024 report evaluated 77 countries, covering 93% of global GDP and 80% of the world's population, providing a comprehensive view of global digital transformation progress. Based on data from reputable third-party sources on digital transformation performance, countries were categorized into three groups: Frontrunners, Adopters, and Starters, each receiving tailored recommendations for advancing their digital development.

Despite all the advantages of the Global Digitalization Index, its main limitations are the restricted country coverage (77 states) and the absence of time-series data, as the index is currently calculated only for 2024. Although 77 countries may seem insufficient, the sample includes states at different levels of development, which makes the index representative in terms of global digital heterogeneity. However, the lack of repeated observations does not allow for a comprehensive assessment of dynamic trends.

Table 1

COMPARISON OF INDICES CHARACTERIZING THE LEVEL OF TRADE DIGITALIZATION

Index	Period Covered	Countries Covered	Data Gaps	Application	Source
AI Index	Since 2017	60+ countries	Data may be missing for countries with limited AI usage	Tracks development, deployment and regulation of AI – relevant for innovations in digital trade	Stanford University (n.d.)
Digital Economy and Society Index	Since 2014	27 EU countries	Primarily covers EU countries	Measures the digitalization level of economy and society, including connectivity, digital services, and skills; identifies strengths and challenges in EU digitalization	European Commission (n.d.)
Digital Economy Rankings	It was published as a one-off study in 2010	About 100 countries	Outdated after 2010	Reflects the growing impact of ICT on economic and social progress	Economist Intelligence Unit (2010)
Digital Evolution Index	Since 2015	60+ countries	Gaps exist for certain countries	Analyzes the evolution of the digital economy, digital opportunities and limitations of countries	Digital Planet & Tufts University (n.d.a)
Digital Intelligence Index	Since 2017	About 90 countries	Gaps exist for certain countries	Measures digital transformation, the readiness of the population and businesses for digital innovations	Digital Planet & Tufts University (n.d.b)
Digital Readiness Index	Since 2017	146 countries	Some indicators may be missing for countries with limited data access	Measures countries' digital readiness, including infrastructure, technology, and digital skills of population; supports the analysis of the potential for integration into the global digital economy	Cisco (n.d.)
Doing Business Ranking	2004-2020	About 190 countries	Gaps exist for certain countries	Evaluates the regulatory environment for doing business, which are necessary for analyzing regulatory barriers in digital business	World Bank Group (n.d.a)

E-Government Development Index	Since 2001	193 countries	Gaps exist for certain countries	Assesses e-government development and readiness to provide digital services	United Nations (n.d.)
Global Competitiveness Index	Since 1979 (modernized in 2018)	140+ countries	Gaps exist for smaller countries	Evaluates technological development and innovation capacity, which are critical for digitalization infrastructure	World Economic Forum (n.d.a)
Global Connectivity Index	2014–2020	79 countries	Possible gaps exist for smaller countries	Analyzes network connectivity levels and impact of digital infrastructure on economic activity	Huawei (n.d.)
Global Digitalization Index	Since 2024	77 countries	Available for only one year for 77 countries	Tracks digitalization levels of economies, including the adoption of technologies in business and society	Huawei (2024)
Global Innovation Index	Since 2007	130+ countries	In some years, data gaps may be observed for certain countries	Assesses countries' innovation potential considering economic, scientific, and technological aspects; useful for analyzing digital innovation in international trade	World Intellectual Property Organization (n.d.)
ICT Development Index	2009–2017, resumed in 2023	190+ countries	Incomplete coverage for some countries	Assesses ICT infrastructure, availability, and skills – foundation for analyzing access to digital resources	International Telecommunication Union (n.d.)
Networked Readiness Index	Since 2002 (modernized in 2016); 2017–2018 data not available	120+ countries	Data gaps exist for certain years and countries	Assesses countries' readiness to leverage networked technologies for economic growth	World Economic Forum (n.d.b), since 2019 – Portulans Institute (n.d.)
World Digital Competitiveness	Since 2017	67 countries	Gaps exist for certain countries	Assesses the ability of countries to adopt and exploit digital technologies for economic growth and competitiveness	IMD World Competitiveness Center (n.d.)

Therefore, it was necessary to identify another index that would be methodologically close to the GDI but provide broader temporal coverage. For this reason, indices with a number of observed countries close to 70 or more, and with continuous data over at least the last decade, were selected: the E-Government Development Index, the World Digital Competitiveness Index, the Global Innovation Index, and the Digital Intelligence Index with its sub-indices. Correlation analysis was then conducted to determine which of these indices most closely aligns with the GDI (see Table 2).

Table 2

CORRELATION BETWEEN DIGITAL INDICES AND THE GLOBAL DIGITALIZATION INDEX

<table>
<tr><th colspan="2">Index</th><th>Correlation</th></tr>
<tr><td colspan="2">E-Government Development Index</td><td>0.790</td></tr>
<tr><td rowspan="6">Digital Intelligence Index</td><td>Digital Evolution: State</td><td>0.948</td></tr>
<tr><td>Digital Evolution: Momentum</td><td>-0.061</td></tr>
<tr><td>Digital Trust: Environment</td><td>0.699</td></tr>
<tr><td>Digital Trust: Behavior</td><td>0.067</td></tr>
<tr><td>Digital Trust: Attitude</td><td>0.196</td></tr>
<tr><td>Digital Trust: Experience</td><td>0.857</td></tr>
<tr><td colspan="2">Global Innovation Index</td><td>0.948</td></tr>
<tr><td colspan="2">World Digital Competitiveness</td><td>0.896</td></tr>
</table>

Among the examined indicators, the Global Innovation Index demonstrated the highest correlation with the GDI (0.948), equal to the Digital Evolution: State sub-index of the Digital Intelligence Index (0.948), and exceeding the World Digital Competitiveness Index (0.896) and the E-Government Development Index (0.790). Other sub-indices of the Digital Intelligence Index showed significantly lower correlations, making them less suitable for capturing the dynamics of digital transformation. Therefore, the Global Innovation Index was chosen as the primary indicator for further analysis, as it ensures methodological consistency with the Global Digitalization Index and provides substantially broader temporal and geographical coverage.

As stated in the description of the methodology, modeling in accordance with the stated goals requires factors related to digitalization, macroeconomic indicators, and determinants of countries' competitiveness in terms of export performance. A comprehensive resource for collecting such data is the World Bank's World Development Indicators database (World Bank Group, n.d.b). From this database, 15 primary indicators were selected to characterize the level of digitalization and macroeconomic parameters for 133 countries (according to the number in the Global Innovation Index reports) over the period 2011–2023. The lower bound of 2011 was chosen because from this year onward the data coverage across indicators and countries becomes more complete and methodologically consistent, which ensures reliable cross-country comparisons. The upper bound of 2023 reflects the most recent year for which information is available, thereby allowing the analysis to capture the latest trends in global digital transformation.

Specifically, 16 indicators were used: the Global Innovation Index and its sub-indices (Institutions, Human Capital and Research, Infrastructure, Market Sophistication, Business Sophistication, Knowledge and Technology Outputs, Creative Outputs); GDP per capita (current U.S. dollars); Military expenditure (% of GDP); Inflation, GDP deflator (annual %); Mobile cellular subscriptions (per 100 people); Population ages 65 and above (% of total population); Rural population (% of total population); Urban population (% of total population); GNI per capita (Atlas method, current U.S. dollars); GNI, PPP (current international dollars); GDP (current U.S. dollars); Total population; High-technology exports (% of manufactured exports); Trade (% of GDP); Merchandise trade (% of GDP); and Services trade (% of GDP). In addition, data on the export and import of goods and services were collected, based on which two separate indicators were calculated for each country: the share of goods exports in total merchandise trade (1) and the share of services exports in total services trade (2).

Due to the lack of data for certain years or for the entire observation period for specific countries, some were excluded from the analysis. In cases of partial data absence, imputation methods were applied, including calculating the mean value for the relevant country group and extrapolating trends based on time series. The use of relative indicators was also justified, as this allows for accurate comparisons between countries with different economic scales. On this basis, a final dataset of 7 indicators (the list can be seen in Table 3) was compiled for 128 countries across 13 years (2011–2023), with adjustments for missing data. At this stage, a correlation analysis was conducted in order to examine the relationships between the selected variables and to assess the potential risks of multicollinearity.

Table 3

CORRELATION MATRIX BETWEEN DIGITALIZATION FACTORS AND MACROECONOMIC INDICATORS

	Share of goods exports (%)	Share of services exports (%)	Global Innovation Index	GDP per capita (current U.S. dollars)	Military expenditure (% of GDP)	Inflation, GDP deflator (annual %)	Mobile cellular subscriptions (per 100 people)
Share of goods exports (%)	1						
Share of services exports (%)	-0.283	1					
Global Innovation Index	0.321	0.335	1				
GDP per capita (current U.S. dollars)	0.382	0.129	0.780	1			
Military expenditure (% of GDP)	0.148	-0.135	-0.024	0.029	1		
Inflation, GDP deflator (annual %)	-0.010	-0.096	-0.130	-0.084	-0.031	1	
Mobile cellular subscriptions (per 100 people)	0.369	0.185	0.398	0.328	0.209	-0.075	1

The results in Table 3 confirm that the explanatory variables do not exhibit excessive correlations with one another, thereby minimizing multicollinearity risks and ensuring the validity of subsequent models.

Cluster analysis of digital development and international trade characteristics of countries

In order to group countries according to their digital development and international trade characteristics, clustering analysis was applied. This approach makes it possible to identify groups of countries with similar profiles and to reveal patterns of global development. After testing several clustering options, the division into six clusters was found to provide the most appropriate balance between statistical robustness and economic interpretability (see Fig. 1). The chosen configuration ensures that countries can be meaningfully classified by development level and differentiated by their positions in global innovation indices and export structure.

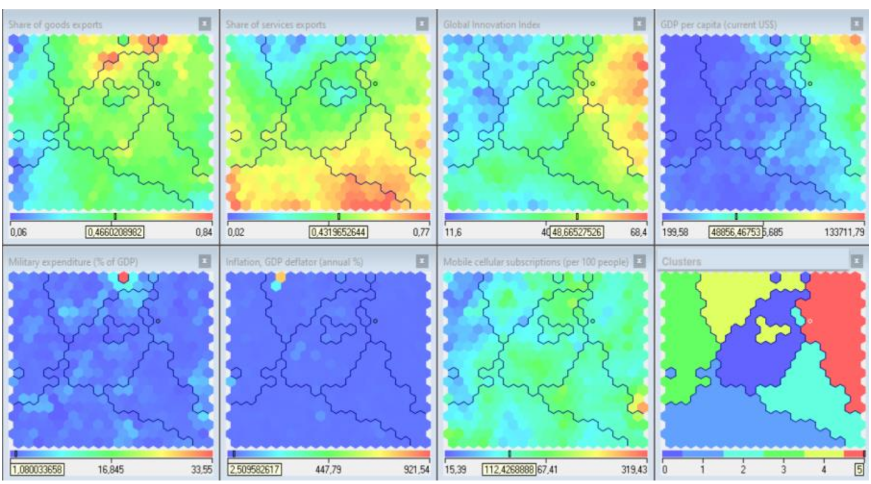

Fig. 1. Distribution of countries by clusters based on digitalization and macroeconomic indicators

The obtained results, presented on the Kohonen map, clearly demonstrate the distribution of countries into several clusters with distinct characteristics. As is typical for this method, the strongest and weakest countries are positioned in opposite corners of the map, which makes it possible to visually identify the extremes. At the same time, the clusters are not arranged in a direct order from weakest to strongest, but are intermingled, reflecting a more complex structure of similarities and differences. Intermediate clusters fill the space between the extremes, showing gradual variations in the level of economic development, integration into global trade, and innovation activity. Within this structure, as can be seen in Fig. 2, Ukraine's cluster membership over the years illustrates shifts in its position – at times improving, at times worsening – reflecting the dynamics of its foreign economic performance.

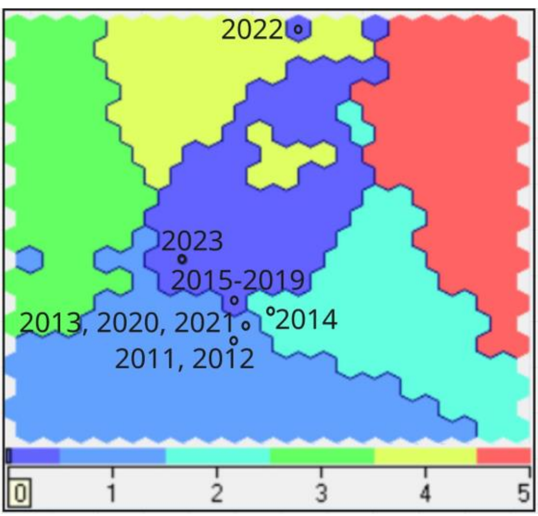

Fig. 2. Ukraine's positions on the SOM during 2011–2023

Additionally, Table 4 provides a detailed overview of the countries and their respective cluster assignments (note that the cluster number can be identified by the color and corresponding number on the ruler below the map in Fig. 2).

Table 4

DISTRIBUTION OF COUNTRIES BY CLUSTERS AND YEARS OF MEMBERSHIP (2011–2023)

Cluster	Countries and years of membership in the cluster
Cluster 0	Argentina (2011-2023); Azerbaijan (2015-2019, 2021); Bahrain (2019-2023); Bolivia (2022); Botswana (2011-2019, 2022, 2023); Brazil (2011-2023); Cambodia (2020); Chile (2011-2020, 2023); China (2011-2020, 2023); Colombia (2011-2023); Ecuador (2013-2019); Ghana (2012, 2015-2019, 2021); Indonesia (2011-2023); Iran (2016-2023); Kazakhstan (2015-2023); Kuwait (2015-2023); Malaysia (2016-2023); Mexico (2011-2023); Mongolia (2014, 2015); Namibia (2013, 2016-2018); Paraguay (2011-2014, 2021); Peru (2011-2019); Qatar (2016, 2017, 2021); Russia (2011-2023); Slovakia (2011, 2022, 2023); South Africa (2011-2023); Thailand (2011, 2012, 2020-2023); Trinidad and Tobago (2011-2015); Ukraine (2015-2019, 2022, 2023); United Arab Emirates (2011-2015); Uruguay (2013, 2014, 2018-2023); Vietnam (2011-2019, 2022, 2023); Zambia (2012)
Cluster 1	Albania (2011-2023); Armenia (2011-2023); Belarus (2011-2023); Bolivia (2011-2019, 2023); Bosnia (2011-2023); Cambodia (2011-2019, 2023); Costa Rica (2011-2023); Croatia (2011-2023); Dominican Republic (2011-2023); Egypt (2011-2014, 2023); El Salvador (2011-2023); Georgia (2011-2023); Greece (2011-2023); Guatemala (2011-2019); Honduras (2011-2019); India (2011-2023); Jamaica (2011-2020, 2022, 2023); Jordan (2011-2019, 2021-2023); Kenya (2011-2022); Kyrgyzstan (2017, 2019); Latvia (2022); Lebanon (2011-2016); Mauritius (2011-2023); Moldova (2011-2023); Montenegro (2011-2023); Morocco (2011-2023); Namibia (2011-2019); Nicaragua (2012-2023); North Macedonia (2011-2023); Panama (2011-2023); Paraguay (2015-2020); Philippines (2011-2023); Romania (2011, 2012, 2019-2023); Serbia (2011-2023); Sri Lanka (2013-2019, 2022, 2023); Tunisia (2011-2023); Turkey (2011-2023); Ukraine (2011-2013, 2020, 2021); United Republic of Tanzania (2013-2023); Uruguay (2011)
Cluster 2	Bahrain (2011-2018); Bulgaria (2011-2023); China (2021, 2022); Cyprus (2011-2023); Czech Republic (2011-2023); Estonia (2011-2023); Hungary (2011-2023); Italy (2011-2023); Latvia (2011-2021, 2023); Lithuania (2011-2023); Malaysia (2011-2015); Malta (2011-2023); Poland (2011-2023); Portugal (2011-2023); Romania (2013-2018); Slovakia (2012-2021); Slovenia (2011-2023); Spain (2011-2023); Thailand (2014-2019); Ukraine (2014); United Arab Emirates (2016-2023); Uruguay (2012, 2015-2017)

Cluster 3	Bangladesh (2011-2013, 2017-2023); Benin (2011-2023); Burkina Faso (2011-2023); Burundi (2011-2023); Cambodia (2022); Cameroon (2011-2023); Egypt (2015-2022); Ethiopia (2011-2023); Guatemala (2020-2022); Honduras (2020-2023); Jamaica (2021); Jordan (2020); Kenya (2023); Kyrgyzstan (2011-2016, 2018, 2020-2023); Lebanon (2017-2023); Madagascar (2011-2023); Malawi (2020-2022); Nepal (2011-2023); Nicaragua (2011); Niger (2011-2023); Pakistan (2011-2023); Paraguay (2022, 2023); Rwanda (2011-2023); Senegal (2011-2023); Sri Lanka (2011, 2012, 2020, 2021); Tajikistan (2011-2023); Togo (2011-2023); Uganda (2011-2023); United Republic of Tanzania (2011, 2012); Zambia (2015, 2016); Zimbabwe (2011)
Cluster 4	Algeria (2011-2023); Azerbaijan (2011-2014, 2020, 2022, 2023); Bangladesh (2014-2016); Bolivia (2020, 2021); Botswana (2020, 2021); Brunei Darussalam (2011-2023); Cambodia (2021); Chile (2021-2023); Cote d'Ivoire (2011-2023); Ecuador (2011, 2012, 2020-2023); Ghana (2011, 2013, 2014, 2020, 2022, 2023); Guinea (2011-2023); Indonesia (2021, 2022); Iran (2011-2015); Kazakhstan (2011-2014); Kuwait (2013-2023); Mali (2012-2023); Mongolia (2011-2023); Mozambique (2016-2018); Namibia (2023); Nigeria (2011-2023); Oman (2012-2023); Peru (2020-2023); Saudi Arabia (2011-2023); Trinidad and Tobago (2016-2023); Vietnam (2020, 2021); Zambia (2011, 2013, 2014, 2017-2023); Zimbabwe (2011-2023)
Cluster 5	Australia (2011-2023); Austria (2011-2023); Belgium (2011-2023); Canada (2011-2023); Denmark (2011-2023); Finland (2011-2023); France (2011-2023); Germany (2011-2023); Hong Kong (2011-2023); Iceland (2011-2023); Ireland (2011-2023); Israel (2011-2023); Japan (2011-2023); Luxembourg (2011-2023); Netherlands (2011-2023); New Zealand (2011-2023); Norway (2011-2023); Qatar (2011-2015, 2018-2020, 2022, 2023); Republic of Korea (2011-2023); Singapore (2011-2023); Sweden (2011-2023); Switzerland (2011-2023); United Kingdom (2011-2023); USA (2011-2023)

As Table 4 shows, the most advanced economies, including the G7 members, the EU core, and the developed countries of East Asia, are concentrated in Cluster 5 (in the upper right corner of Fig. 2), characterized by high GDP per capita, strong innovation potential, and deep digital integration (as evidenced, for example, by the high levels of GDP per capita, Global Innovation Index, and Mobile cellular subscriptions in the corresponding heatmaps in Fig. 1).

Cluster 0 in the central part of Fig. 2 brings together rapidly developing emerging markets such as Brazil, China, Indonesia, South Africa, and Vietnam. Ukraine also fell into this cluster during periods of its active development. These countries demonstrate relatively high GDP growth potential, supported by increasing innovation capacity and digital penetration, while still maintaining moderate shares of goods and services sectors – features typical of economies in transition toward more diversified structures.

Cluster 1, in the lower-left part of Fig. 2, consists mainly of countries from the Balkans, the Caucasus, parts of the Middle East, and Latin America, characterized by a high share of services exports, comparatively low intensity of goods export and GDP per capita. Given the relatively low level of digitalization, this pattern indicates limited industrial competitiveness and uneven integration into global value chains.

Cluster 2, in the lower-right corner of the map, brings together EU economies with GDP per capita below the European average but a significant share of services exports, including Bulgaria, Czech Republic, Italy, Lithuania, Poland, Spain, etc., forming an intermediate group between the advanced Cluster 5 and the middle-performing Cluster 1. At the opposite end of the SOM, Cluster 3 includes the least developed economies of Africa and Asia, such as Bangladesh, Cambodia, Ethiopia, Nepal, Tajikistan, marked by very low GDP per capita, innovation levels, and limited mobile connectivity.

Cluster 4, which neighbors it, combines resource-dependent countries (e.g., Algeria, Chile, Kazakhstan, Saudi Arabia) with medium GDP per capita but low diversification, reflected in a dominant share of goods exports and a low share of services exports, along with low innovation rates. In addition, this cluster included countries with the highest inflation.

As for Ukraine, from 2011 to 2013 (before the russia's annexation of Crimea and the outbreak of hostilities in eastern Ukraine), it belonged to Cluster 1, which unites countries characterized by (see Fig. 1):

1. A predominant share of services exports over goods exports, indicating the growing importance of non-material trade components.

2. A below-average GDP per capita and average GII values, reflecting a transitional level of technological development.

3. Stable, but not advanced, digital connectivity, as evidenced by the average mobile cellular subscriptions.

In 2014, Ukraine shifted to Cluster 2, which unites several EU economies with higher trade openness, following the Revolution of Dignity and the overthrow of the authoritarian regime of Yanukovych. The transition to this cluster is driven by growing share of goods exports (due to rapprochement with the EU), which led to a higher degree of trade balance. But this reclassification coincided with a sharp decline in GDP per capita, a surge in inflation and military expenditure, which was caused by the first wave of russian military invasion of Ukraine.

In 2015–2019, clustering placed Ukraine in the group of countries with dynamic growth and broad integration into the global economy (Cluster 0). This cluster characterized by moderate GDP per capita, gradual improvement in innovation and digital connectivity (GII and mobile subscriptions), and balanced trade structures combining goods and services exports. Ukraine's inclusion in this group can be explained by macroeconomic stabilization following the 2014–2015 crisis and improved export competitiveness driven by the hryvnia devaluation. Between 2015 and 2019, inflation remained high but controllable, military expenditures stabilized, and innovation indicators slightly improved, reflecting a shift toward a more resilient economic model. Thus, in 2015–2019 the structure of Ukraine's economy and trade began to approach that of large economies, combining a strong industrial sector with the gradual expansion of digital component.

The global crisis of 2020–2021, triggered by the COVID-19 pandemic, affected countries in different ways. During this period, Ukraine's GDP per capita increased from 3,751 to 4,827 in current U.S. dollars; however, the share of services in exports remained almost unchanged (around 56–58%), while the Global Innovation Index slightly declined. These factors explain why, according to the Kohonen map (see Fig. 2), the country returned to Cluster 1 – a group characterized by average innovation capacity, and an unbalanced trade structure with a strong predominance of services exports over goods exports. In this group, the digital component of trade (proxied by innovation and connectivity indicators) was still at an intermediate rather than advanced level. Thus, Ukraine's clustering during 2020–2021 reflects the persistence of a transitional model, combining moderate digital readiness with a services-oriented but not yet innovation-driven trade pattern.

It's worth noting that although Ukraine shifted between three clusters from 2011 to 2021, topologically it remained in one central region of the Kohonen map, moving between neighboring neurons. However, in 2022, there was a sharp jump to another part of the map, caused by russia's full-scale military invasion. And although Ukraine formally moved back to Cluster 0, it was already an isolated neuron in the middle of the fourth cluster at the top of the map. Its key feature was the highest military spending as a percentage of GDP, which soared to 33.5% in 2022, as well as an increase in inflation to almost 35%. In 2023, Ukraine remained in the same cluster but moved closer to the center of the map, reflecting some stabilization after the outbreak of war.

Thus, a distinctive feature of the early war period was that, despite the nominal increase in GDP per capita to 5,181 in current U.S. dollars in 2023, real economic activity contracted due to war-time disruptions. At the same time, the share of services in exports has fallen sharply – from 0.56 in 2021 to 0.39 in 2023, indicating a return to the dominance of goods in external trade. This dynamic explains Ukraine's relocation on the SOM to Cluster 0, alongside large emerging economies such as Brazil, Mexico, South Africa, and Vietnam, as well as resource-oriented exporters Chile, Kazakhstan, Malaysia, etc. This shift does not imply an improvement in performance, but rather a structural convergence with countries combining an industrial export base, strong inflationary and fiscal pressures, and mid-level digital development. Ukraine's economy in this period became more similar to such models due to the war-driven compression of the service sector, high military spending, and reliance on external financial support to sustain macroeconomic stability.

Thus, the transition from Cluster 1 to Cluster 0 during 2020–2023 reflects a dual nature of the Ukrainian economy: resilience of digital sectors coexisting with heightened macroeconomic fragility. The clustering results emphasize that the country's position was shaped not by GDP dynamics alone, but also by the interaction between digital capacity, export composition, and inflationary shocks.

Construction of models for forecasting the dynamics of international trade of countries in the same cluster as Ukraine

In line with the overall aim of this study – to examine the impact of digitalization, innovation and other factors on the transformation of international trade – this subsection focuses on the predictive aspect of the research. Building on the preceding clustering of countries, the next step is to construct forecasting models based on data for countries within a specific cluster that capture their inherent interactions between digital factors and trade performance. It serves two purposes: first, to assess the potential trajectories of Ukraine's international trade in goods and services under the influence of digital transformation; and second, to project the country's position within global digital indices such as the Global Innovation Index.

When forecasting Ukraine's future development and forming management scenarios for shaping the digital economy to achieve set goals (particularly in terms of international trade), it is essential to rely on the current situation (there is no point in building a forecast based on Ukraine's position several years ago). Therefore, the database on which predictive models will be built should be based on data for countries in the cluster in which Ukraine was most recently located (in 2023).

It's important to note that in recent years, Ukraine has been part of Cluster 0, where it was located during the most competitive periods of its development, sharing it with large emerging economies. These countries are characterized by relatively strong industrial base, diversification efforts, and a growing share of digital services in exports. Using their trajectories as a benchmark allows for evidence-based forecasting of Ukraine's potential development paths, since they provide comparable structural conditions and external challenges. However, the development scenarios that can serve as a basis for the formulation of policy recommendations should primarily consider the dynamics of those economies that demonstrated resilience and digital growth while being in the same cluster with Ukraine, ensuring consistency and methodological robustness.

To construct predictive models, regressions and neural networks were applied, allowing for the consideration of both linear and potentially nonlinear dependencies. As substantiated in the Methodology section, the Share of goods exports and the Share of services exports were treated as dependent variables, while the Global Innovation Index, GDP per capita, military expenditures, inflation, and the number of mobile cellular subscriptions served as independent variables. Note that all explanatory variables were considered with a one-year lag relative to the dependent variables, since the effects of innovation, household income, and macroeconomic indicators usually materialize with some delay.

Regression predictive models

Primarily, regression models were built, the first of which was for forecasting the Share of goods exports. The formalized representation of such a model has the form:

$$\widehat{Y_0} = 50.738 - 0.092X_1 + 0.0003X_2 + 0.949X_3 + 0.080X_4 + 0.001X_5, \quad (3)$$

where $\widehat{Y_0}$ – forecast of the Share of goods exports, X_1 – Global Innovation Index, X_2 – GDP per capita, X_3 – Military expenditure, X_4 – Inflation (GDP deflator), X_5 – Mobile cellular subscriptions.

The coefficient of determination (R^2 = 0.185) of regression (3) indicates that approximately 18.5% of the variation in the Share of goods exports is explained by the selected factors, indicating its complete inadequacy. This is also confirmed by Fig. 3, which shows the actual and projected values of the share of goods exports for different countries and years within the sample.

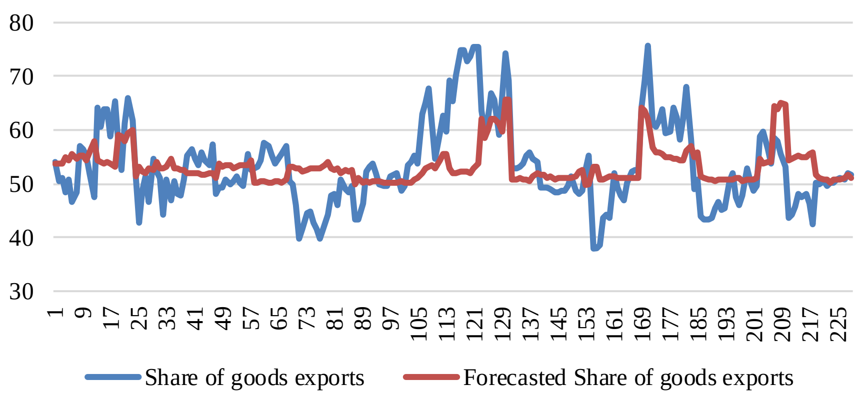

Fig. 3. Regression forecasting the Share of goods exports

Despite the obviously low forecast accuracy, the F-test value ($F = 10.15$, $p < 0.001$) indicates the model's significance. Therefore, we will conduct an analysis of regression coefficients. It demonstrates that the Global Innovation Index does not have a statistically significant effect on the Share of goods exports ($\beta = -0.0917$, $p = 0.295$). In contrast, GDP per capita shows a strong and statistically significant positive impact ($\beta = 0.0003$, $p < 0.001$), implying that higher income levels contribute to an increased Share of goods exports. Similarly, military expenditures exert a positive and significant effect ($\beta = 0.9490$, $p = 0.012$), indicating that higher defense spending may stimulate industrial output and, consequently, goods exports. Inflation also has a positive coefficient ($\beta = 0.0802$) and approaches statistical significance ($p = 0.058$), suggesting that moderate increase in domestic prices may accompany export expansion. Finally, mobile cellular subscriptions display an insignificant relationship ($\beta = 0.0011$, $p = 0.957$), implying that digital infrastructure, while relevant for services, has a limited direct influence on goods export dynamics in this sample.

For the services exports model, all explanatory variables were also lagged by one year to account for the delayed impact on the outcome variable. The accuracy of this model is generally consistent with model (3). Specifically, the Share of services exports forecasting model is statistically significant as a whole ($F = 6.27$, $p < 0.001$), although the coefficient of determination is unacceptably low ($R^2 = 0.123$). This model can be specified as follows:

$$\widehat{Y_1} = 46.404 - 0.134X_1 - 0.0001X_2 - 1.139X_3 - 0.014X_4 + 0.017X_5, \quad (4)$$

where $\widehat{Y_1}$ – forecast of the Share of services exports.

In model (4), the Global Innovation Index shows a negative but statistically insignificant effect on the Share of services exports ($\beta = -0.1336$, $p = 0.108$), suggesting that innovation activity alone does not directly translate into higher services export performance, possibly due to structural barriers or differences in innovation absorption across economies. In contrast, GDP per capita exerts a statistically significant negative influence ($\beta = -0.0001$, $p = 0.009$), implying that higher income levels lead to a gradual shift from services exports to imports (the Share of services exports decreases).

Similarly, military expenditures have a highly significant negative impact (β = –1.1385, p = 0.0015), indicating that increased defense spending may limit resources available for productive and export-oriented service sectors. Meanwhile, inflation (β = –0.0141, p = 0.724) and mobile cellular subscriptions (β = 0.0165, p = 0.407) do not show statistically significant relationships with the dependent variable, suggesting that short-term macroeconomic fluctuations and the expansion of digital connectivity have limited direct effects on services exports within the analyzed sample.

Fig. 4 visually shows the discrepancy between actual and forecasted values of the Share of services exports based on linear regression, which indicates the inability of the model (4) to reflect the general dynamics of services exports based on the selected factors.

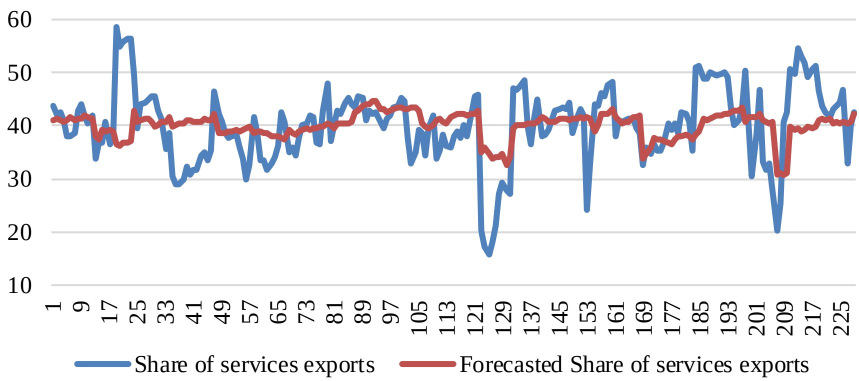

Fig. 4. Regression forecasting the Share of services exports

To summarize the analysis of the effectiveness of regression models in forecasting the shares of goods and services exports, it can be assumed that the inadequacy of these models is due to their linear nature and small number of parameters, which did not allow for the identification of complex patterns between indicators of trade, innovation, digitalization, and macroeconomics. Therefore, we will try to build more accurate models based on neural networks of perceptron type, taking into account their ability to identify nonlinear patterns and a large number of adjustable parameters.

Neural network forecasting

The neural network models in our study were constructed using the same principle as the regression models – five indicators were used to forecast the shares of exports of goods and services: the Global Innovation Index, GDP per capita, Military expenditure, Inflation, GDP deflator, and Mobile cellular subscriptions (per 100 people). Accordingly, the inputs of the neural network are 5 neurons to which these independent variables are fed, and the output layer has one neuron with the corresponding output variable.

The input and output neurons are connected through a single hidden layer, the number of neurons in which was determined after testing several alternative architectures. The choice of a compact architecture was determined by the limited size of the empirical base, which restricts the applicability of more complex multilayer models. Sigmoid activation functions were employed, as they are suitable for detecting nonlinear dependencies in datasets.

Figs. 5 and 6 schematically represent the neural network architectures that yielded the highest accuracy in predicting the Share of

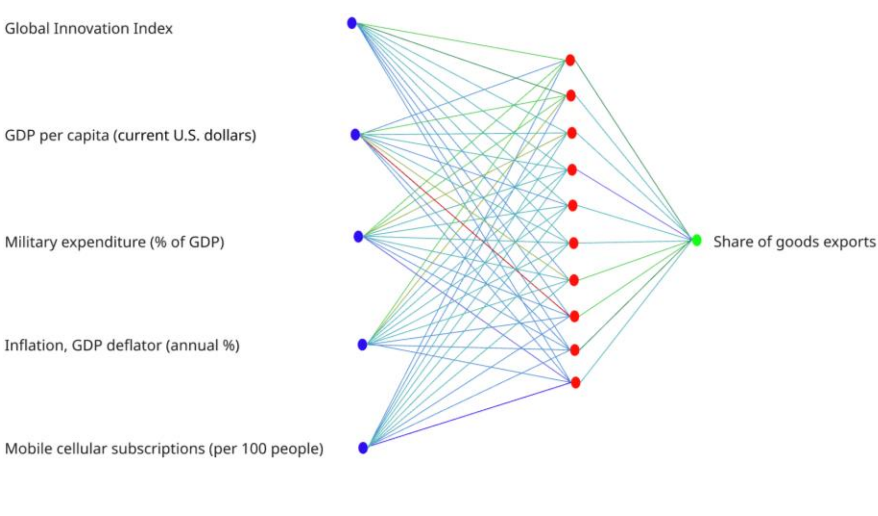

Fig. 5. Neural network model for forecasting the Share of goods exports based on digitalization and macroeconomic indicators

goods exports in total goods trade and the Share of services exports in total services trade, respectively.

Blue nodes represent input variables, green nodes represent output indicators, while the central red nodes are the neurons of the hidden layer, which aggregate the relationships detected by the model. The color of the connecting lines indicates the weight of the connections between the neurons, by which it is possible to determine the degree of influence of the selected factors on the trade structure (weights vary from blue to red, the values of which can be seen in the colored bar below the figure).

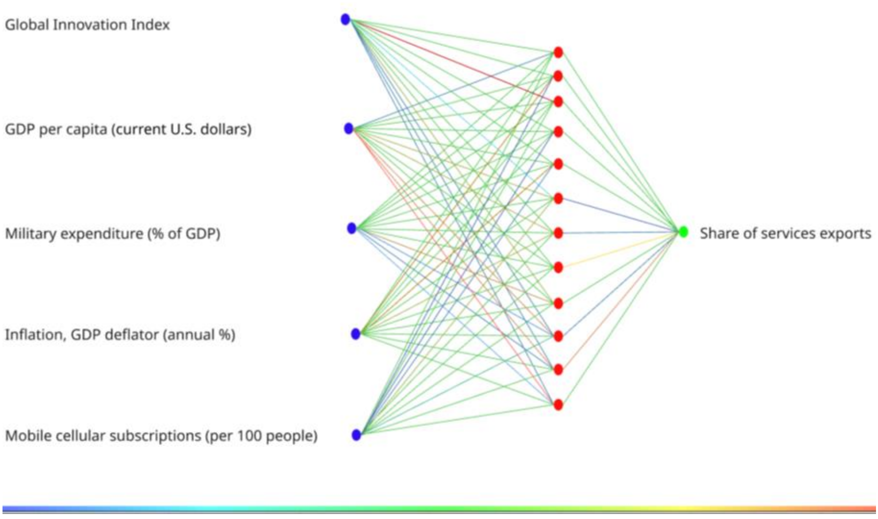

Fig. 6. Neural network model for forecasting the Share of services exports based on digitalization and macroeconomic indicators

As can be seen from Fig. 5, a perceptron with a single hidden layer consisting of 10 neurons was selected as the optimal network structure for predicting the Share of goods exports. The prediction by this neural network on the training set can be seen in Fig. 7. To model the Share of services exports, a single-layer perceptron with 12 neurons in the hidden layer was chosen. Its prediction on the training data is presented in Fig. 8.

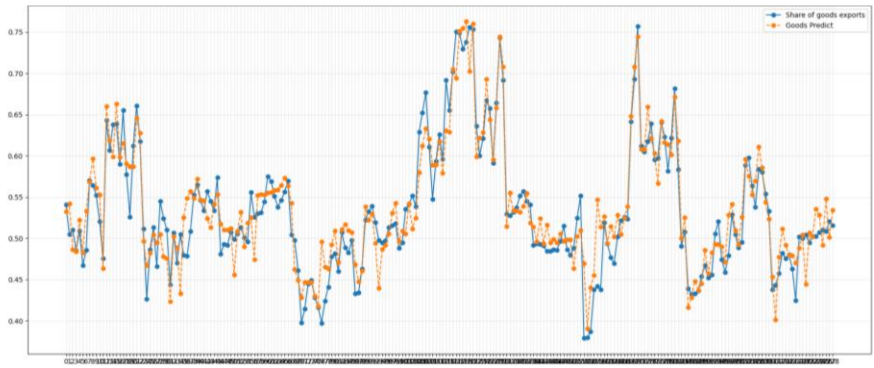

Fig. 7. Neural network forecasting of the Share of goods exports

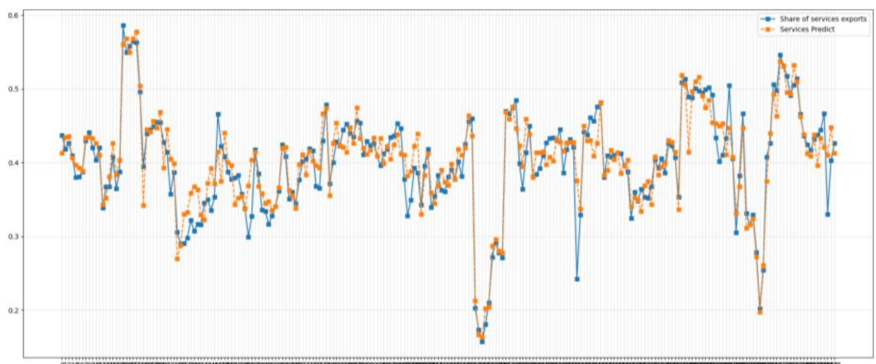

Fig. 8. Neural network forecasting of the Share of services exports

The coefficient of determination of the neural network presented in Fig. 5, when predicting the indicator the Share of goods exports on the training sample, shown in Fig. 7, is $R^2 = 0.870$, which significantly exceeds the accuracy of the corresponding regression model (3).

For the neural network presented in Fig. 6, the coefficient of determination was $R^2 = 0.866$ when predicting the indicator the Share of services exports on the training sample (see Fig. 8), while for the regression model (4) $R^2 = 0.123$.

This comparison demonstrates a clear improvement in accuracy when using the neural networks, which better capture nonlinear dependencies between digitalization and macroeconomic indicators, resulting in more precise estimations of both goods and services export shares. These findings highlight the importance of employing machine learning approaches in analyzing international trade structures and assessing the influence of diverse factors. However, the use of these neural network models to predict the corresponding indicators for Ukraine showed significantly lower forecast accuracy. In particular, the coefficient of determination when predicting the Share of goods exports was 0.186, and for the Share of services exports – 0.439. This indicates insufficient predictive ability of the models on data on which the model was not trained.

Overall, the results indicate that digital and macroeconomic factors jointly shape trade structure, generally adequately reflecting overall trends in goods and services exports and demonstrating statistical reliability within the sample of countries. At the same time, the moderate predictive power suggests that the structure of international trade is influenced by a broader range of economic, institutional, and digital factors. Future research will aim to further understand these factors, which, together with the characteristics of digitalization, determine foreign trade indicators.

Conclusions

The conducted research suggests that digitalization and innovation contribute to the ongoing transformation of international trade. Within this study, the level of digitalization of countries was assessed based on relevant indices and macroeconomic indicators, and their impact on the dynamics of goods and services exports as well as overall development was analyzed. The results allow us to formulate several general conclusions.

To assess the level of digitalization, the Global Digitalization Index would be appropriate, as it reflects the key dimensions of digital transformation and enables cross-country comparisons. However, its limitations lie in the absence of time series data (it only covers 2024) and the restricted coverage of only 77 countries. The correlation analysis between the GDI and 14 other indices (E-Government Development Index, World Digital Competitiveness Index, Digital Intelligence Index, etc.) showed that the highest correlation with GDI has the Global Innovation Index, which justifies its use as a proxy for modeling the level of digitalization of countries on more extensive datasets.

A total of 16 primary indicators were initially selected from the Global Innovation Index reports and the World Development Indicators database to characterize the level of digitalization and macroeconomic parameters of 133 countries from 2011 to 2023 (the period of maximum database completeness). A correlation and regression analysis of the relationships between digital, economic and trade indicators was conducted to identify the factors to be used in further research. A final dataset of 7 indicators for 128 countries over 13 years was compiled, using imputation method in cases of missing data. The correlation analysis allowed us to exclude highly correlated indicators to avoid multicollinearity and thereby ensure the reliability of subsequent estimations.

Using the Self-Organizing Maps (SOM) approach, countries were grouped according to their level of digital maturity and economic development over a 13-year period. Clustering was applied to identify groups of economies with similar structural characteristics and ensure that the forecasting models were based on comparable digital and innovation environments across the countries selected for their construction. This methodological step made it possible to reveal cross-country convergence trends and to better interpret the determinants of international trade structures.

Over the analyzed period, Ukraine moved across three clusters, remaining mostly near the central zone of the SOM – an area that corresponds to countries with moderate innovation performance and partial digital integration, such as Poland, Romania, and Turkey. A temporary shift to another area of the map, though within the same cluster, coincided with the onset of Russia’s full-scale military invasion, which disrupted economic stability and digital connectivity.

The country's current cluster affiliation indicates an ongoing stage of structural transformation, combining institutional volatility with a strong potential for modernization and reintegration into global digital markets.

To ensure structural comparability, forecasting models were built using data from countries within the same cluster. Regression analysis and neural network methods were used, with the shares of exports of goods and services serving as dependent variables, and digitalization and macroeconomic indicators as independent variables. A series of experiments were conducted to select the optimal model architecture that would ensure the highest forecasting accuracy.

The results confirmed that digital and macroeconomic factors jointly influence trade structure. Neural network modeling, in particular, captured nonlinear relationships more effectively, demonstrating their statistical robustness within the sample of countries used to train the models. At the same time, the moderate predictive power for new data that was not involved in training the models indicates that the structure of international trade is shaped by a broader range of economic, institutional, and digital factors.

Overall, the obtained results highlight that Ukraine's trade transformation depends not only on digital readiness and innovation capacity but also on the broader macroeconomic and institutional environment. Future research should extend this framework by incorporating post-war recovery dynamics, cross-border digital policies, and global value chain participation to enhance the understanding of Ukraine's digital trade trajectory and its long-term integration prospects.

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