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Global Digital Convergence: Impact of Cybersecurity, Business Transparency, Economic Transformation, and AML Efficiency

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Abstract: The article substantiates the existence of convergence processes in the field of digitization of countries, taking into account the number of Internet users; people with advanced skills; and indicators of infrastructure (network coverage, population covered by at least a 3G mobile network, population covered by at least a 4G mobile network), access (access to ICT at home, active mobile broadband subscriptions, fixed broadband subscriptions), enablers (fixed broadband over 10 Mbps, mobile data and voice basket, high consumption) and barriers (improved broadband access from 256 kbps to 2 Mbps and from 2 Mbps to 10 Mbps mobile data and voice basket, low consumption) of digital development. The methodological basis for determining the sigma convergence of digitization processes is the coefficient of variation. The values of the coefficient of variation confirmed the high level of convergence between the studied countries in terms of the degree of use of the Internet for conducting digital transactions. The developed econometric model, which describes the influence of statistically significant integral indicators of the national cybersecurity level, ease of doing business, and the anti-money laundering index on the country's digital development level, made it possible to determine the average trend of dependence on the level of digital development. One hundred four countries were considered for the analysis. The conducted study of the impact of digitalization on economic transformations based on developed quantile regressions made it possible to analyze exactly how the level of digital development for countries with a high level of digitalization and for countries with a low level of digitalization development depends on the value of the national cybersecurity indicator and the ease of doing business, and which countries have the least resistance to the risk factors of their involvement in fraudulent schemes for the purpose of legalizing criminal income.

Keywords: economic development; digital development level; national cybersecurity; economic transformations; sigma convergence; quantile regression

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1. Introduction

Financial and economic systems increasingly depend on many digital systems and big data. This upward trend allows socio-economic objects to exist. Understanding the key ideas of the global digital economy guarantees the stable functioning of the financial system [1]. In this regard, there are many problems and issues related to, firstly, the trust in digital systems; secondly, determining the strength of digital trust to combine business [2], politics, public, social, and personal information; and thirdly, determining the impact of key indicators on digital evolution [3], considering the global pandemic [4–6]. The purpose of the article is (1) to determine the sigma convergence for countries regarding the number of people who use Internet services and (2) to develop a multifactor regression model for describing the impact of key determinants that shape the level of risk of using financial instruments for money laundering and terrorist financing (Basel AML Index), business aspects (ease of getting electricity, ease of doing business), and national cybersecurity level (National Cyber Security Index) on the digital development level. The objectives of the article are the application of economic and mathematical techniques that allow the development of quantile regressions. The central objective is to determine how the values of national cybersecurity and ease of doing business for countries with high levels of digital development affect digital development and how the importance of national cybersecurity and ease of doing business for countries with low levels of digital development affect digital development.

According to the results of the analysis of the world scientists' publishing activity, based on articles indexed in the Scopus database, it is possible to conclude that the topic "digital development and cybersecurity" is of great interest. Thus, based on a sample of 89 publications generated by the Scopus database search engine over the past five years, a bibliometric analysis was conducted using ScientoPy software and Python. The study revealed the 10 most used keywords on "digital development and cybersecurity", determined their percentage in the total number of publications (Figure 1), calculated the average growth rate (AGR) and the average annual number of publications (ADY) with relevant keywords and reflected the Hirsch index (Figure 2), and quantitatively compared scientific papers with the keywords found until 2020 and during 2020–2021.

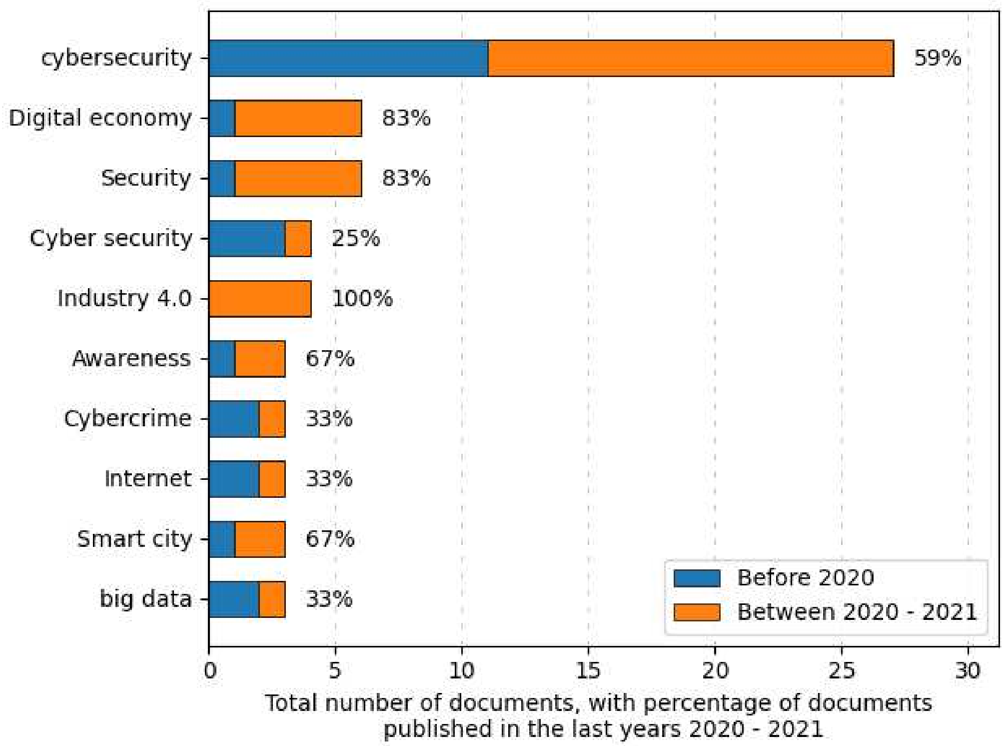

Figure 1. Bibliographic analysis by keywords of publishing activity in terms of research "digital development level and cybersecurity". Source: built by the authors using ScientoPy software tools based on a sample of Scopus database publications.

Thus, during 2020–2021, the value of the keyword "fourth industrial revolution" (Industry 4.0) is 100%, i.e., scientists mentioned it in all 89 selected publications on "digital development and cybersecurity" (Figure 1). The use of the keywords "digital economy" and "security" is 83%; the keywords "awareness" and "smart city", 67%; "cybersecurity" 59%; "cyber security", 25%; and "big data", "Internet", and "cybercrime", 33%.

No	AuthorKeywords	Total	Average Growth Rate (AGR)	Average documents per year (ADY)	h-index
1	cybersecurity	27	2.5	8.0	5
2	digital economy	6	1.0	2.5	3
3	security	6	1.0	2.5	2
4	cyber security	4	−0.5	0.5	2
5	industry 4.0	4	2.0	2.0	1
6	awareness	3	0.0	1.0	2
7	cybercrime	3	0.5	0.5	2
8	Internet	3	−0.5	0.5	1
9	smart city	3	0.0	1.0	2
10	big data	3	−0.5	0.5	1

Figure 2. Calculation of paper statistics. Source: developed by the authors using ScientoPy and Python software tools based on a sample of Scopus database publications.

The statistics from Figure 2 for the period from 2020 to 2021 show a list of the 10 most used keywords, their total number in the sample of bibliometric research on the query "digital development and cybersecurity", the Hirsch index, the average growth rate for keyword use in found publications, and the average number of publications per year. For example, the highest value of the Hirsch index is 5 for the keyword "cybersecurity", the average number of references (AGR) to this keyword in publications is 2.5, and the average annual number of publications is eight units (ADY), which corresponds to 59.3% compared to other keywords (Figure 2). So, the bibliometric analysis of 89 publications indexed by the Scopus database in 2020 and 2021 confirms that the top keywords (Figure 2) belong to the research topic.

It is necessary to emphasize the work of Ghernaouti-Helie, S. [7], where at the social level, the author studied key issues, barriers, and components that contribute to cybersecurity by reviewing certain fundamental concepts. The works [8–11] in which the authors examine the relationship between the current, dynamic climate of organizational cyber risk, cybersecurity effectiveness, and changes in cybersecurity investment to identify the epistemic climate for intellectual capital management represented by cybersecurity dynamics and AML efficiency are also of great interest. Of great interest is the work of scientists Batrancea et al. [12], in which the authors examine the transparency of the banking system and indicators of economic growth in the period from 1990 to 2019 using the example of seven countries that are not members of the Basel Committee on Banking Supervision. The authors of [12] proved, based on the developed econometric model, that economic growth proxied by gross domestic product growth rate was mainly driven by bank capital to assets ratio across the three decades.

Data mining methods using machine learning [13] and powerful statistical methods have become very popular research tools [14–16]. One such method is quantile regression, which allows a detailed analysis of the studied indicators and their response to risk factors and stress testing. The range of use and mathematical tools implemented in the development of quantile regressions are shown in Figure 3. The analysis was performed using VOSviewer bibliometric tools based on a sample of 1575 publications obtained from the Scopus database for "applications of quantile regressions". The six clusters are grouped by the number of keywords that match five or more publications. Thus, from the total number of 9262 keywords in the observed publications, 596 links were formed (Figure 3).

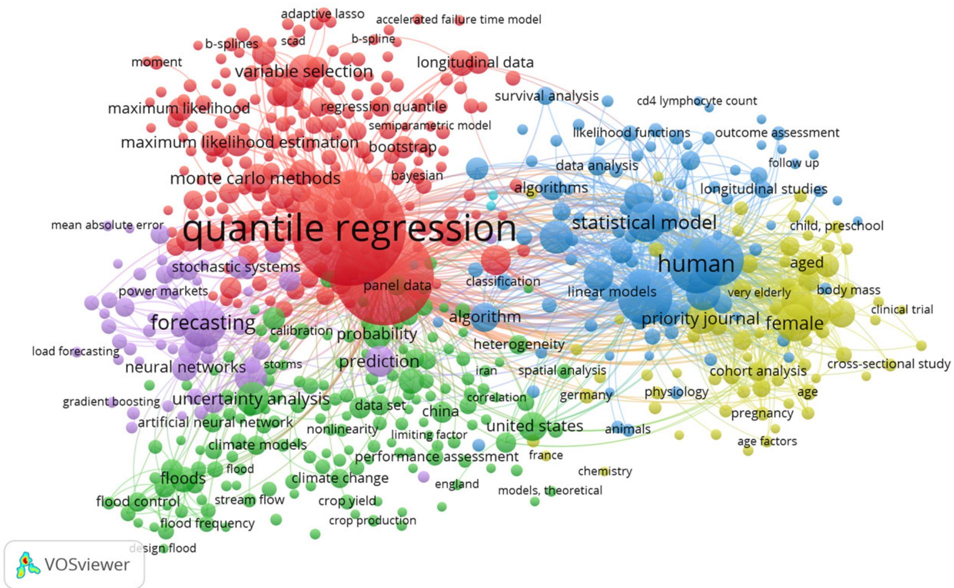

Figure 3. Bibliographic analysis of quantile regression use. Source: developed by the authors using VOSviewer tools.

2. Materials and Methods

The first stage in this study of the impact of socio-economic transformation digitalization on digital development is to determine the sigma convergence level regarding the number of people in 66 countries who use the Internet in everyday life. The Internet is the environment where digital relationships and interconnections are formed. It enables the implementation of digital operations in various directions (financial [17–20], social [21–23], political [24–27], technological [28,29]) and serves as a lure for fraudsters and their use of various sophisticated fraudulent schemes in data theft and finance [30–32].

The classical definition of σ-convergence is characterized by a decrease in the dispersion of income per capita between countries over time [33]. From the economic point of view, the convergence hypothesis is used to test the effect of catching up with the economic growth of developing countries with low per capita income to the level of developed countries with high per capita income. The source of the study of conditional convergence between countries with different levels of economic development arose with the investigation of the Solow exogenous growth model [34] in the 1960s, based on exogenous savings and neoclassical production function. The model proves that countries far from the steady state (a state in which labor capital is at a constant level [35]) have higher economic growth rates than countries closer to it. Conditional convergence implies that countries with low economic development will develop faster than rich countries and eventually reach their prosperity level, provided that the structural parameters of their economies are the same [36].

For determining the impact of socio-economic transformations and digitalization on digital development, taking into account risk indicators of financial institutions for money laundering and indicators characterizing the national cybersecurity level, the second stage is the application of multidimensional statistical analysis tools to develop a multiple regression model of the influence of indicators National Cyber Security Index, ease of getting electricity, ease of doing business, and Basel AML Index on the digital development level.

In the third stage, nonlinear optimization and multidimensional statistical analysis tools are used to develop quantile regressions to determine how national cybersecurity indicators and ease of doing business for high-digital countries affect digital development and how national cybersecurity indicators and ease of doing business for countries with low levels of digital development affect the overall level of digital development and, consequently, the global level of the country's digital development.

Quantile regression, first described in 1978, is a convenient and flexible tool for risk management [37], stress testing, and financial economics. However, now, approaches to its development are being modified and improved [38].

One should note that linear and quantile regression, which generalize median regression, solve different issues. If the classical regression investigates what factors change the average value of the dependent indicator at fixed regressors, the median regression investigates what the median of the dependent indicator depends on. In this case, the estimates of the coefficients may be different for classical and median regression but capable and statistically significant for both types of models since hypotheses are similarly tested:

$$t = \frac{\hat{\beta}_j - \beta_j}{se} \rightarrow N(0,1),\ se = \frac{s}{\sqrt{n}}\,, \tag{1}$$

where $\hat{\beta}_j$ is the regression coefficient estimate, β_j is the real value of the coefficient, se is the standard mean error, s is the standard deviation of a random variable based on an unbiased estimate of its sample variance, and n is the sample size.

One can asymptotically confirm that the random variable t, calculated as the ratio of the difference between the estimated regression coefficient $\hat{\beta}_j$ and its true value β_j to the standard mean error se, obtains the normal standard random value.

The method of determining confidence intervals is also similar. However, the calculation of regression coefficients of estimates $\hat{\beta}_j$ and standard errors of estimates $\hat{\beta}_j$ is significantly different for classical and median regression. There are different formulas for its calculation.

The quantile regression generalizes the median regression. The peculiarity of the proposed methodology for the quantile regression development is that, firstly, it is not based on assumptions about the target variable distribution. Secondly, it is more resistant to emission observations than multiple linear regression. Quantile regression simulates the relationship between a set of variable predictors (independent indicators) and specific percentiles or quantiles of the target variable.

The median is a quantile equal to 50%; i.e., 50% of observations are below the median:

$$P(y_i \leq Med(y_i)) = 0.5\,, \tag{2}$$

where $Med(y_i)$ is the median of the dependent variable y_i, the probability of observations.

The quantile of the order τ_i is calculated by Formula (3) and defines such a number that the probability of falling to the left of it is equal to τ:

$$P(y_i \leq q_\tau) = \tau, \tag{3}$$

where τ is the probability of falling to the left of the defined number and q is the quantile.

A quantile equal to 0.25 is also called the lower quartile or percentile. It describes such a value of the variation series x_p that 25% of the values of the variational series take values less than or equal to the number x_p.

So, indicators for 2021 covering 104 countries were used as input indicators for developing a regression model describing the level of digitalization: digital development level [39], National Cyber Security Index [40], ease of getting electricity [41], ease of doing business [41], and Basel AML Index [42].

The descriptive analysis (Table 1) using the Statgraphics 19 software confirmed the statistical quality of the characteristic space of the research indicators.

Table 1. Numerical characteristics of digital development level, national cybersecurity, ease of doing business, and AML efficiency.

Numerical Characteristic	Values of Numerical Characteristics				
	DDL	NCSI	TINY	SEES	Basel AML Index
Count	104	104	104	104	104
Average	54.8756	52.8471	75.8846	69.326	5.25731
Median	56.4	53.25	79.9	71.3	5.065
5% trimmed mean	55.4666	52.9025	76.591	69.7953	5.22462
5% Winsorized mean	55.2919	52.8722	76.1769	69.5558	5.23865
Variance	342.765	579.173	244.579	112.98	1.51524
Standard deviation	18.5139	24.066	15.639	10.6292	1.23095
Coeff. of variation,%	33.738	45.539	20.609	15.3322	23.4141
Gini coefficient	0.192863	0.263678	0.115213	0.0866507	0.132998
Standard error	1.81544	2.35987	1.53353	1.04228	0.120704
5% Winsorized sigma	19.2252	26.1713	16.2096	10.8941	1.24947
Mean absolute deviation	15.361	0.463934	0.1829	0.132682	0.191382
MAD	13.45	18.19	8.95	8.3	0.815
Sbi	18.9432	25.1447	15.7102	10.7724	1.25407
Minimum	0	10.39	33.8	40.7	2.68
Maximum	84.17	96.1	100.0	86.8	8.49
Range	84.17	85.71	66.2	46.1	5.81
Lower quartile	42.025	34.415	64.6	61.15	4.47
Upper quartile	68.47	71.43	87.1	77.35	6.06
Interquartile range	26.445	37.015	22.5	16.2	1.59
1/6 sextile	34.56	25.97	58.6	59.1	3.98
5/6 sextile	76.23	79.22	89.2	79.7	6.5
Intersextile range	41.67	53.25	30.6	20.6	2.52
Skewness	−0.391986	−0.0484368	−0.718956	−0.611812	0.370877
Stnd. skewness	−1.63197	−0.201659	−2.99325	−2.54718	1.54408
Kurtosis	−0.433026	−1.05311	−0.126493	−0.296931	−0.244463
Stnd. kurtosis	−0.901416	−2.19222	−0.263317	−0.618111	−0.50889
Sum	5707.06	5496.1	7892.0	7209.9	546.76
Sum of squares	348,483	350,108	624,073	511,470	3030.55

Source: developed by the authors.

As we can see from Table 1, the coefficient of variation is greater than 5% for all indicators, so all indicators are statistically significant.

3. Results

3.1. Defining the Sigma Convergence of the Digital Processes

Given that data are a new economic resource of the 21st century and that digital data development is the engine of economic development, it is reasonable to determine the sigma convergence regarding the indicator (the total number of billions of persons) of the number of people around the global Internet services. The information base used the study results of the International Telecommunication Union [43]. The period is 20 years, namely the range from 2000 to 2020.

The countries under study are Albania, Austria, Bahrain, Belarus, Belgium, Bolivia, Bosnia and Herzegovina, Bulgaria, Cambodia, Chad, China, Costa Rica, Croatia, Cyprus, Czech Republic, Denmark, Egypt, Estonia, Finland, Georgia, Germany, Greece, Hong

Kong, China, Hungary, Indonesia, Iran, Ireland, Kazakhstan, Korea, Kuwait, Latvia, Lithuania, Luxembourg, Malaysia, Malta, Mauritius, Mexico, Mongolia, Montenegro, Morocco, Netherlands, Northern Macedonia, Norway, Oman, Paraguay, Peru, Poland, Portugal, Qatar, Romania, Russian Federation, Saudi Arabia, Serbia, Seychelles, Singapore, Slovakia, Slovenia, Spain, Sweden, Taiwan, Thailand, Turkey, Ukraine, United Arab Emirates, Great Britain, and Vietnam. The sample covers both countries with a high level of economy and countries with a low level of economy.

Such inequality indicators as the Herfindahl–Hirschman index, Tayle index, and Gini index are most often used to test the hypothesis regarding the presence or absence of sigma convergence (sigma divergence) in terms of economic growth. However, it is proposed to use the variation indicator to be independent of the input sample size and to transfer the logic of determining the sigma convergence to the digitization indicator—the number of Internet service consumers. Based on the coefficient of variation (Figure 4), we can conclude that there is σ-convergence if this indicator falls over time. Formula (4) is used to calculate the coefficient of variation:

$$CV = \frac{SD_{sample}}{Mean} \times 100\% = \frac{\sqrt{\sum_{i=1}^{n} \frac{(x_i-\mu)^2}{n-1}}}{\mu} = \frac{\sqrt{\sum_{i=1}^{n} \frac{(x_i-\mu)^2}{n-1}}}{\frac{\sum_{i=1}^{n} x_i}{n}}, \tag{4}$$

where SD_{sample} is the standard deviation of the sample from 66 countries, μ is the mean, n is the number of all data points, and x_i is the number of Internet users for the i-country.

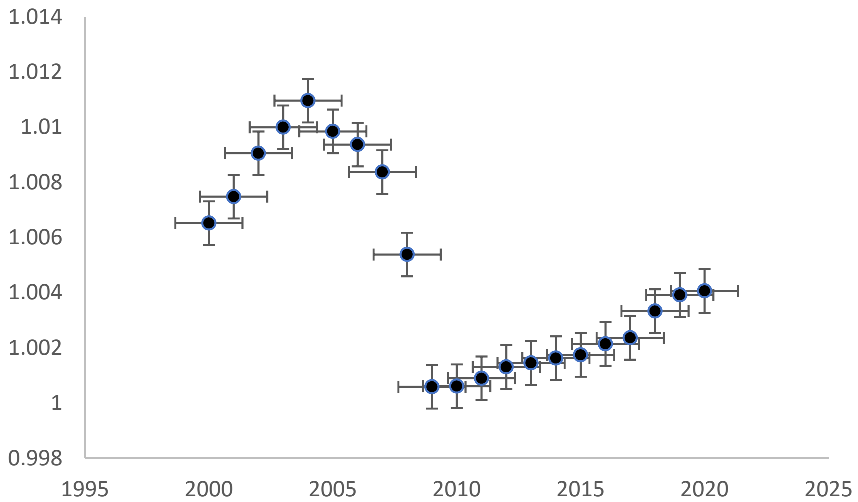

Figure 4. Dynamics of the coefficient of variation. Source: developed by the authors.

Formula (4) uses a sample variance, calculated for a sample of 66 countries.

Vertical and horizontal segments for the value of the coefficient of variation (Figure 4) show the allowable limits of error. The decline in the coefficient of variation indicates a high level of convergence in the studied countries in the degree of Internet use by individuals in 2009–2010. According to the study sample, the lowest coefficient of variation is during these years. From 2011 to 2020, CV gradually increased, but the sigma-convergence index remains relatively high for the studied countries regarding the number of people using the Internet. The increased variation rate relates to the peculiarities of organizing Internet communication and the financial capabilities of citizens of the studied countries. Thus, if we compare the digital development infrastructure and the features of access to the network of all countries [39], the dynamics for some of them significantly differ. A comparative description of indicators of infrastructure, access, opportunities, and barriers for Poland, Ukraine, Germany, and Cyprus is given in Table 2.

Table 2. Indicators of infrastructure, access, enablers, and barriers of digital development.

Indicator/Country	Poland	Ukraine	Germany	Cyprus
Network Coverage	100%	100%	100%	100%
Population covered by at least a 3G mobile network	100%	89%	98%	100%
Population covered by at least a 4G mobile network	100%	87%	100%	100%
ICT access at home (households with a computer at home)	90%	66%	92%	93%
Active mobile-broadband subscriptions per 100 inhabitants	197	89	91	118
Fixed broadband subscriptions per 100 inhabitants	22	19	43	37
Fixed broadband (% of total): 256 kbit/s–<2 Mbit/s	0%	1%	0%	0%
Fixed broadband (% of total): 2 to 10 Mbit/s	9%	4%	5%	2%
Fixed broadband (% of total): >10 Mbit/s	79%	94%	93%	97%
Total fixed broadband subscriptions	8,212,601	7,769,401	36,040,739	332,080
Mobile data and voice basket (high consumption) as a % GNI p.c.	0.9%	1.8%	0.9%	1.4%
Mobile data and voice basket (low consumption) as a % GNI p.c.	0.8%	1.6%	0.9%	0.9%
Fixed broadband basket as a % GNI p.c.	1.3%	1.6%	1.0%	0.9%
Mobile fixed broadband basket as a % GNI p.c.	0.2%	1.5%	0.4%	0.9%
Individuals with advanced skills	5%	1%	5%	4%

Source: developed by the authors based on [43].

It is necessary to conduct a further detailed analysis of what factors affect a country's digital development and to what extent they affect it, provide an opportunity to identify risk factors for using financial institutions for money laundering, and assess how well cybersecurity and anti-fraud are organized in countries.

3.2. Multiple Regression Model Development

As input indicators for the development of a regression model to describe the digitization level, indicators for 2021, covering 104 countries, are used: digital development level (DDL) [40], National Cyber Security Index (NCSI) [40], ease of getting electricity (TINY) [41], ease of doing business (SEES) [41], and Basel AML Index [42]. These indicators are already aggregated according to the appropriate methodology of institutions, which officially determine and publish statistical reports on these indicators. DDL and NCSI are determined according to the methodology of the e-Governance Academy (EGA [40]), which was founded in 2002. It is a non-profit consulting organization that develops a knowledge base of best practices in e-government. *DDL* values are calculated as the arithmetic mean of the ICT Development Index (*IDI*), determined by the International Telecommunication Unit and the Networked Readiness Index (*NRI*) [44] (an indicator that characterizes the development of information technology and network economy in the world):

$$DDL = \frac{IDI\% + NRI\%}{2}. \quad (5)$$

The generalized value of the NCSI is formed based on the score features of 46 indicators, divided into 12 factors according to three categories (Tables 3–5). An example of the distribution by factors for Ukraine is given in Figure 5.

Table 3. General cybersecurity indicators (category 1).

Factor	Cybersecurity Policy Development	Cyber Threat Analysis and Information	Education and Professional Development	Contribution to Global Cybersecurity
Indicator	Cybersecurity policy unit	Cyber threat analysis unit	Cyber safety competencies in primary or secondary education	Convention on cybercrime
Indicator	Cybersecurity policy coordination format	Public cyber threat reports are published annually	Bachelor's level cybersecurity program	Representation in international cooperation formats
Indicator	Cybersecurity strategy	Cyber safety and security website	Master's level cybersecurity program	International cybersecurity organization hosted by the country
Indicator	Cybersecurity strategy implementation plan		PhD level cybersecurity program	Cybersecurity capacity building for other countries
Indicator			Cybersecurity professional association	

Source: developed by the authors based on [40].

Table 4. Baseline cybersecurity indicators (category 2).

Factor	Protection of Digital Services	Protection of Essential Services	E-Identification and Trust Services	Protection of Personal Data
Indicator	Cybersecurity responsibility for digital service providers	Operators of essential services are identified	Unique persistent identifier	Personal data protection legislation
Indicator	Cybersecurity standard for the public sector	Cybersecurity requirements for operators of essential services	Requirements for cryptosystems	Personal data protection authority
Indicator	Competent supervisory authority	Competent supervisory authority	Electronic identification	
Indicator		Regular monitoring of security measures	Electronic signature	
Indicator			Timestamping	
Indicator			Electronic registered delivery service	
Indicator			Competent supervisory authority	

Source: developed by the authors based on [40].

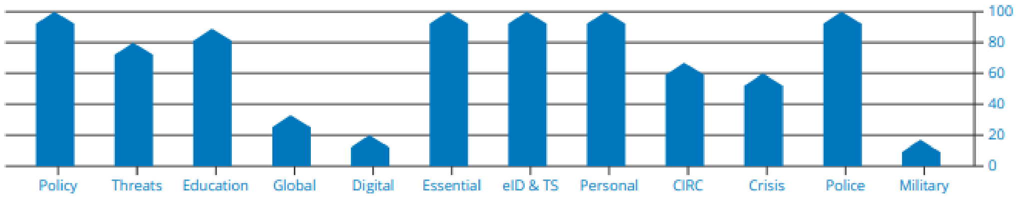

Figure 5. Ukraine: NCSI fulfillment percentages.

Table 5. Incident and crisis management indicators (category 3).

Factor	Cyber Incident Response	Cyber Crisis Management	Fight Against Cybercrime	Military Cyber Operations
Indicator	Cyber incident response unit	Cyber crisis management plan	Cybercrimes are criminalized	Cyber operations unit
Indicator	Reporting responsibility	National-level cyber crisis management exercise	Cybercrime unit	Cyber operations exercise
Indicator	Single point of contact for international coordination	Participation in international cyber crisis exercises	Digital forensics unit	Participation in international cyber exercises
Indicator		Operational support of volunteers in cyber crises	24/7 contact point for international cybercrime	

Source: developed by the authors based on [40].

Thus, indicators that determine the factor of cybersecurity policy development are given by Formula (6)

$$\begin{aligned} &\text{Cyber security policy development} = \\ &\langle \text{Cyber security policy unit, Cyber security policy coordination format,} \\ &\text{Cyber security strategy, Cyber security strategy implementation plan} \rangle \end{aligned} \tag{6}$$

For example, for Ukraine we have the following indicators as of 6 September 2021, according to analytical reports of the e-Governance Academy Foundation [45]: population 42.7 million; area (km^2), 603,700; GGP per capita (USD), 8700; National Cyber Security Index, 24th; Global Cybersecurity Index, 78th; ICT Development Index, 79th; Network Readiness Index, 53rd.

The TINY indicator is found based on the values of such indicators as procedures (number), time (days), cost (% of income per capita), and reliability of supply and transparency of tariff index (0–8) [41].

The SEES indicator is also integrated according to the World Bank's Doing Business methodology and is formed by nine categories measured by values on a 100-point scale (0 is the worst value of the categorical indicator, 100 is the best), namely: ease of starting a business, ease of dealing with construction permits, ease of registering property, ease of getting credit, ease of protecting minority investors, ease of paying taxes, ease of trading across borders, ease of enforcing contracts, ease of resolving insolvency. Category ease of starting a business has such indicators as procedures—men (number), time—men (days), cost—men (% of income per capita), procedures—women (number), time—women (days), cost—women (% of income per capita), and paid-in minimum capital (% of income per capita). The category ease of dealing with construction permits is based on procedures (number), time (days), cost (% of warehouse value), and building quality control index (0–15). The next category, ease of registering property, is defined using procedures (number), time (days), cost (% of property value), and quality of land administration index (0–30). Indicators credit information index, legal rights index, and sum getting credit determine the content of the category ease of getting credit; disclosure index (0–10), director liability index (0–10), shareholder suits index (0–10), shareholder rights index (0–6), ownership and control index (0–7), corporate transparency index (0–7), and strength of minority investors protection index (0–50) are the essence of the category ease of protecting minority investors. The score of the ease of paying taxes category is determined by the values of such indicators as payments (number), time (hours), total tax and contribution rate (% of profit), time to comply with VAT refund (hours), time to obtain VAT refund (weeks), time to comply with corporate income tax audit (hours), time to complete a corporate income tax audit (weeks), and postfiling index (0–100). The category ease of trading across borders is formed by indicators of time to export: border compliance (hours), time to export: documentary compliance (hours), cost to export: border compliance (USD), cost to export: documentary compliance (USD), time to import: border compliance (hours), time to import: documentary compliance (hours), cost to import: border compliance (USD), cost to import: documentary compliance (USD). The category ease of enforcing contracts is defined by the values of indicators time (days), cost (% of claim), and quality of judicial processes index (0–18). The category ease of resolving insolvency is defined by the recovery rate index (cents on the dollar) and strength of insolvency framework index (0–16).

As we can see, many indicators, on the values of which ease of doing business (SEES) indicator is based, are financial inclusion indicators [46], i.e., related to the definition of access to financial services and financial literacy.

The Basel AML Index [42,47] is a comprehensive integrated indicator defined by the Basel Institute for Governance to identify and assess the risks of using countries' financial institutions for money laundering and finance terrorism. Basel AML Index is measured using a 10-point scale: 0 is the best value, the minimum value of risk, indicating risks of corruption and money laundering are absent; 10 is the worst value, the maximum value of risk, indicating that the country is at risk for money laundering. The rating value of the index is determined based on the share of five domains, which specify 17 indicators, namely [47] the quality of anti-money laundering and terrorist financing (quality of AML/CFT framework) (65%), corruption and bribery (corruption and bribery risk) (10%), financial transparency and standards (10%), public transparency and accountability (5%), and political and legal risk (10%).

Thus, the given list of integrated indicators allows us to carry out the complex analysis of the effect made by the factors of social and economic transformation digitalization on a state's digital development.

A fragment of the primary indicators is presented in Appendix A, Table A1.

Since the input indicators, firstly, are already complex and different methodologies considering indices, relative and absolute values of indicators, and scores were used for their convolution, and, secondly, reflect level values (DDL, NCSI) and indices (TINY, SEES, Basel AML Index), it is necessary to carry out their normalization for the possibility of further calculations obtaining significant and adequate results. The final values also depend on the normalization quality. Many scientists worldwide [48–50] suggest normalization based on weights, stimulant indicators (the increase in which has a positive effect on the studied indicator), and disincentive indicators. Therefore, the smallest value of the stimulant or disincentive indicator does not need to correspond to its best value. It depends directly on the content and essence of the indicator. The following weighting coefficients of normalization functions can be used: (1) weights that determine the measures of the central trend of the indicator (median, mode, mean), measures of variability (variance, minimum, maximum value of the variable, scope, asymmetry, and excess); (2) weighted indicators; and (3) scales, which are formed because of expert opinions.

$$y_{ij} = \frac{1}{1 + e^{-3\frac{x_{ij} - p_i}{q_i - p_i}}}, \tag{7}$$

where y_{ij} is the standardized value of the i-country of j-indicator, q_i is the value of the indicator x_{ij} at which the transformation function is at least 0.95, and p_i is the value of the indicator x_{ij} at which the transformation function is 0.5 [51] (Table 6).

Table 6. The values of parameters q_i and p_i for standardization of initial indicators.

Parameter	DDL	NCSI	TINY	SEES	Basel AML Index
$q_i = \max_i x_{ij}$	84.17	96.1	100	86.8	8.49
$p_i = med\left(x_{ij}\right)$	56.4	53.25	79.9	71.3	5.065

Source: calculated by the authors.

A fragment of the normalized indicators is in Appendix A, Table A2.

When establishing a regression model in which the digital development depends on the NCSI, TINY, SEES, and Basel AML Index, it is reasonable to determine the strength of the relationship between them. We propose to find the correlation coefficients using Spearman rank correlation coefficients, where their ranks (not numerical values of these variables) are used to assess the strength of the linear relationship between variables [52]:

$$\rho = 1 - \frac{6}{n(n-1)(n+1)} \sum_{i=1}^{n} (R_i - S_i)^2, \quad (8)$$

where n is the number of observations, R_i is the rank of observation x_i in a row of the variable x, S_i is the rank of observation y_i in a row of the variable y, and $\rho \epsilon [-1; 1]$.

Practical calculations were performed in the applied software Statgraphics 19 using the Describe/Multiple Variable Analysis function. The results are presented in Table 7.

Table 7. Spearman rank correlations.

Indicator	NCSI	DDL	TINY	SEES	Basel AML Index
NCSI		0.7481	0.5081	0.6487	−0.5715
p-Value		0.0000	0.0000	0.0000	0.0000
DDL	0.7481		0.6645	0.8313	−0.6433
p-Value	0.0000		0.0000	0.0000	0.0000
TINY	0.5081	0.6645		0.7120	−0.3782
p-Value	0.0000	0.0000		0.0000	0.0001
SEES	0.6487	0.8313	0.7120		−0.4965
p-Value	0.0000	0.0000	0.0000		0.0000
Basel AML Index	−0.5715	−0.6433	−0.3782	−0.4965	
p-Value	0.0000	0.0000	0.0001	0.0000	

Source: calculated by the authors using Statgraphics 19 software [53].

Table 7 shows Spearman rank correlations between each pair of variables. These correlation coefficients range between −1 and +1 and measure the strength of the association between the variables. In contrast to the more common Pearson correlations, the Spearman coefficients are computed from the ranks of the data values rather than from the values themselves. Consequently, they are less sensitive to outliers than the Pearson coefficients. In addition, the number of pairs of data values used to compute each coefficient is shown in parentheses. The third number in each location of the table is a p-value which tests the statistical significance of the estimated correlations. p-values below 0.05 indicate statistically significant non-zero correlations at the 95.0% confidence level. The following pairs of variables have p-values below 0.05: NCSI and DDL; NCSI and TINY; NCSI and SEES, NCSI and Basel AML Index; DDL and TINY; DDL and SEES; DDL and Basel AML Index; TINY and SEES; TINY and Basel AML Index; SEES and Basel AML Index.

The Basel AML Index is inversely related to all other indicators that are logically justified by the essence of this indicator and the measurement scale. The lowest correlation is observed between the Basel AML Index and TINY (−0.3782), indicating a low correlation, but the correlation value of this indicator with DDL, which is dependent on the regression equation, is high and moderate. The correlation between digital development and all other influential indicators is also relatively high, ranging from 0.6 to 0.8. Next, we consider the regression model. We use the modern statistical package Statgraphics 19, namely the options of the Multiple Regression dialog box, specifying the Backward Stepwise Selection, which checks for multicollinearity of relationships between influential variables. If there are any, it proposes rejecting insignificant variables according to Student and Fisher statistical tests. As a result of calculations, the econometric regression model is received:

$$DDL = 0.249 + 0.3 \cdot NCSI + 0.551 \cdot SEES - 0.32 \cdot Basel\ AML\ Index \quad (9)$$

Since the p-value in the ANOVA Table 8 is less than 0.05, there is a statistically significant relationship between the variables at the 95.0% confidence level. In addition, the statistical significance of model (6) is confirmed by the Student's criterion, the level of significance of the p-value (Table 9), R-squared statistics, and the Durbin–Watson test.

Table 8. Analysis of variance.

Source	Sum of Squares	Df	Mean Square	F-Ratio	*p*-Value
Model	8.77658	3	2.92553	134.04	0.0000
Residual	2.18264	100	0.0218264		
Total (Corr.)	10.9592	103			

Source: calculated by the authors using Statgraphics 19 software [53].

Table 9. Statistic features of model parameters (9).

Parameter	Estimate	Standard Error	T Statistic	*p*-Value
Constant	0.249446	0.0670185	3.72205	0.0003
NCSI	0.300022	0.0670501	4.47459	0.0000
SEES	0.551139	0.0610039	9.03449	0.0000
Basel AML Index	−0.319672	0.0810828	−3.94254	0.0001

Source: calculated by the authors using Statgraphics 19 software [53].

The R-squared statistic, the coefficient of determination, indicates that the model explains 80.084% of the variability of the dependent indicator at the digital development level. The standardized value of the R-squared statistic is 79.4865% and indicates the adequacy and static significance of the econometric multiple linear regression model (9). So, the coefficient of determination, which explains the fraction of the variance of the dependent variable in the regression model and is calculated as the ratio of the regression sum of squares (SSR) to the total sum of squares (SST), allows us to estimate how well the theoretical model agrees with real data if even the dependent variable does not have a normal distribution. Thus, the developed model (6) agrees very well with the initial data. The standard error of the estimate has the standard deviation of the residuals 0.148. The mean absolute error (MAE) is equal to 0.107 and characterizes the average value of the residuals. The Durbin–Watson (DW) test checks the residuals to determine whether there is a significant correlation between the independent variables in the order in which they are entered into the model. The calculated value of the Durbin–Watson test (2.372) is in the range from 0.584 to 2.464, which indicates compliance with the uncertainty zone. Further study of autocorrelation of residues using the John von Neumann test shows its absence; $DW \approx 2$—no autocorrelation [54].

The absence of multicollinearity between the independent variables of the econometric model (9) was proven using the variance inflation factor test (*VIF* test):

$$VIF = \frac{1}{1 - R^2} \quad (10)$$

where R^2 is the coefficient of determination.

Strict *VIF* should be below 3.0 and moderate *VIF* should be below 5.0.

The calculation of the *VIF* test was performed using Excel software (Table 10), which approved the absence of multicollinearity between the independent variables (9).

Table 10. Results of *VIF* test.

			Regression Statistics							
			Multiple R			0.4314				
			R-Squared			0.6705				
			Adjusted R			0.3871				
			Standard Error			0.14737253				
			Observations			104				
	Coefficients	Standard error	t-Stat	p-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%	VIF	R-squared
Intercept	−0.0394	0.0314	−1.2558	0.2121	−0.1016	0.0228	−0.1016	0.0228		
NCSI	0.2987	0.0669	4.4654	0.0000	0.1660	0.4314	0.1660	0.4314	1.9861	0.4965
SEES	0.5497	0.0609	9.0255	0.0000	0.4288	0.6705	0.4288	0.6705	1.8161	0.4494
Basel AML Index	0.2591	0.0645	4.0135	0.0001	0.1310	0.3871	0.1310	0.3871	1.5045	0.3353

Source: calculated by the authors.

3.3. Development of Quantile Regression Models

We conduct a quantile analysis during the third step by developing quantile regressions. In such a way, we describe the NCSI and SEES impact on DDL for countries with high digital development quantiles of the order 0.9 [54,55], and countries with a low digital development quantile of the order 0.1 [56,57], to provide a comprehensive analysis of how digitization affects the inclusive economic growth [58].

The proposed logic for developing quantile regressions for different values of quantiles is based on the following steps.

Step 1. Determining the estimates of the regression coefficients for the quantile of the order of 0.5 using Formula (11) and nonlinear optimization by the gradient descent method:

$$L_\tau = \sum_{i=1}^{n} \rho_\tau (Y_i - \beta X_i) \to \min, \quad (11)$$

where ρ_τ is the "check" loss function, a weight coefficient, the value of which is calculated by the Formula (12):

$$\rho_\tau(a) = \max(\tau a, (\tau - 1)a), \quad (12)$$

where τ is the value of the quantile and a is the model error value.

Step 2. Assessing the error of the model using the covariance matrix and kernel estimation of error density.

Step 3. Determining the standard error, Student's criterion, and level of significance of the p-value based on the covariance matrix values, considering the kernel estimation of the model error density.

The loss function of the simple linear regression is quadratic. We minimize the sum of squares of deviations from the actual value of the response variable and estimate the conditional mean that is the center point of linear regression. Koenker R. has shown that if we minimize absolute deviations, we estimate conditional median. If we use the so-called "check" loss function ρ_τ where tau is any quantile from zero to one (zero percentile being the lowest realization, one being the highest possible realization, 0.5 or 50 being the median).

The software implementation of determining the quantile regression coefficients at quantile values of 0.5, 0.9, and 0.1 is carried out using MS Excel and the Solver add-on. Before using the Solver tool, we must directly calculate the objective function (11) [57].

A fragment of the implementation is presented in Appendix B, Table A3. The sum of the products of the required quantile regression estimates and the true values is used to determine the Forecast column (Appendix B, Table A3). The error value is calculated as the difference between the true values of the digitization level indicator and the predicted values. The column "Loss" values (Appendix B, Table A3) are calculated by the formula (12).

Having used the Solver add-on and using the gradient descent nonlinear optimization method [59], the conditional median regression equation is obtained:

$$DDL = -0.013 + 0.344 \cdot \text{NCSI} + 0.71 \cdot \text{SEES}. \tag{13}$$

Then, it is necessary to go to step 2 and estimate the error of the model using the covariance matrix (14) and the function of kernel estimation of the distribution density ((15) and (16)) [60].

$$C_\tau = \frac{\tau(1-\tau)}{f_E^2\left(F_E^{-1}(\tau)\right)}\left(X^T X\right)^{-1}, \tag{14}$$

where $f_E(x)$ is the kernel estimation of error density (KDE):

$$f_E(x) = \frac{1}{hn}\sum_{i=1}^{n} K\left(\frac{x-x_i}{h}\right), \tag{15}$$

where $h > 0$ and represents the bandwidth, n is the sample size, and K is the weighted core (weight function):

$$h = 0.9 \min\left(\sigma_E, \frac{IQR_E}{1.34}\right) n^{-1/5}, \tag{16}$$

where IQR_E is the interquartile range (robust scatter measure calculated using percentiles).

We should note that the Student's distribution is used to find K (15). However, depending on the purpose of the study, different kernel functions (homogeneous, triangular, three-weighted, normal, etc.) can be used. The parameter h is a free smoothing parameter. It strongly affects the evaluation result, so other formulas usually calculate it; the smaller the bandwidth value, the better. An alternative formula for determining the value of bandwidth may be the following Formula (17):

$$MISE(h) = E\left[\int \left(\hat{f}_h(x) - f(x)\right)^2 dx\right], \tag{17}$$

where $MISE(h)$ is the mean integrated squared error and $\hat{f}_h(x)$ is the assessment of kernel density.

Therefore, the intermediate values calculated using the built-in MS Excel functions to find the covariance matrix and further determine the statistical significance of the conditional median Equation (12) are presented in Table 11.

Table 11. Intermediate calculations.

Indicator	Result	Formula of Calculation	Location in Cell of Excel Sheet
Total loss	5.5557	Formula (11)	
Quantile	0.5		B8
n (sample size)	104	=COUNT(C21:C124)	B9
h (bandwidth)	4.22%	=0.9 × MIN(B12;B13) × B9^(−1/5)	B10
Error quantile	0.00%	=PERCENTILE.XLC(H21:H124;B8)	B11
Standard deviation	16%	=STDEV.S(C21:C124)	B12
IQR/1.34	12%	=(PERCENTILE.XLC(H21:H124;0.75) − PERCENTILE.XLC(H21:H124;0.25))/1.34	B13
Kernel density	3.65	=SUM(J21:J124)/(B9 × B10)	B14

Source: calculated by the authors.

The kernel distribution function for the studied countries using Formula (16) and the built-in MS Excel functions is T.DIST (B $ 11-H21)/B $ 10; B $ 9–3; 0).

The error quantile indicator, equal to zero or close to it, characterizes the correctness of the calculations that determine the estimates of NCSI and SEES with Solver and gradient descent. Next, it is necessary to calculate the covariance matrix (14). The array formula and built-in MS Excel functions are used. The dimension of the covariance matrix will be 3 × 3, determined by the values of Constant, NCSI, and SEES for 104 studied countries (range D21: F124). The formula to be entered in the MS Excel formula row is as follows:

$$\{=B8 \times (1 - B8)/B14\hat{}2 \times \mathrm{MINVERSE}(\mathrm{MMULT}(\mathrm{TRANSPOSE}\ (D21{:}F124);D21{:}F124))\}. \quad (18)$$

The keyboard shortcut Ctrl + Shift + Enter is used to obtain the resulting covariance matrix. The calculation results of the covariance matrix used to estimate the errors of the KDE model are presented in Table 12.

Table 12. Covariance matrix.

Covariance	Constant	NCSI	SEES
Constant	0.0007	−0.0007	−0.0004
NCSI	−0.0007	0.0034	−0.0021
SEES	−0.0004	−0.0021	0.0031

Source: calculated by the authors.

The third step is to verify the significance of the quantile regression of the order 0.5 (12). The test results are presented in Table 13.

Table 13. Verification of the statistical significance of the model (13).

	Constant	NCSI	SEES
Coefficient	−0.01309	0.34442434	0.710076991
Standard error	0.026743	0.058207857	0.055426417
t-stat	−0.48936	5.91714517	12.81116536
p-value	62.57%	0.00%	0.00%

Source: calculated by the authors.

The covariance matrix (Table 12) enables quickly determining the standard error as the square root of the elements of the main diagonal and the value of the Student's criterion (t-stat) as the ratio of model coefficients (13) to standard error. The *p*-value is calculated using the T.DIST.2T function:

$$p\text{-value} = \text{T.DIST.2T(ABS(D4);\$B8} - 3). \quad (19)$$

When analyzing the results, it is obvious that the *p*-value for a free member exceeds the maximum allowable 5% and does not give objective estimates.

The proposed methodology will be used to develop quantile regressions of orders 0.9 and 0.1. They characterize the numbers of countries with high (quantile 0.9) and low (quantile 0.1) levels of digital development to determine how the NCSI and SEES indicators affect the formation of digital development.

The general results of the study are presented in Table 14.

Table 14. Equation of quantile regressions regarding the impact of national cybersecurity indicators and ease of doing business on a country's digital development.

	Constant	NCSI	SEES
	(1) Quantile 0.5		
DDL	−0.0131	0.3444	0.7100
p-value	62.57%	0.00%	0.00%
	(2) Quantile 0.9		
DDL	0.26403	0.3707	0.4711
p-value	0.00%	0.01%	0.00%
	(3) Quantile 0.1		
DDL	−0.0722	0.1952	0.6433
p-value	4.95%	1.66%	0.00%

Source: calculated by the authors.

4. Discussion

Thus, model (9) can be practically implemented by domestic and international institutions that study national cybersecurity and ease of doing business to identify opportunities to increase the NCSI and SEES, which have a directly proportional positive impact on digital development. For example, if the NCSI indicator increases by 1%, while the values of the SEES and Basel AML Index remain at the average level, the overall digital development level will increase by 0.003 (0.3%). If the SEES indicator increases by 1%, provided that the NCSI and Basel AML Index indicators remain at the average level, the digital development will increase by 0.00551 (0.55%). The relationship between digital development and the Basel AML Index is inversely proportional because the lower the Basel AML Index, the less the country is at risk of exposing its socio-economic objects (especially banks, non-banks, financial institutions, enterprises, and businesses) to fraudulent schemes using digital technologies or to the use of innovative financial technologies for money laundering.

All quantile regression coefficients for the 10th percentile and the 90th percentile are statistically significant. However, the constant at the 10th percentile (Table 14 (3)) (quantile 0.1) is negative (–7.13%). So if other things are held equal (if NCSI and SEES are zeros) then the 10% of the countries with low digitalization will have a slightly negative dynamic of reactions on risk factors.

For countries with a high level of digital development, corresponding to the 90th percentile, the model (Table 14 (2)) (quantile 0.9) has positive coefficients. The constant is relatively high and equal to 26.4%. If the value of the national cybersecurity indicator changes by 1 point, the value of digital development will increase by 0.26. With an increase in the indicator of ease of doing business by 1 point, the value of digital development will increase by 0.37. It is a positive factor in raising the global cybersecurity index is usually a positive factor in raising the global cybersecurity index [61].

It should also be noted that the values of the coefficients of quantile regressions (Table 14) depend on the type of function in Formula (15) and the definition of the parameter h (bandwidth), but the quality of the obtained models should be checked using the Student's test and the p-value [62].

For further research on the national cybersecurity level, it is advisable to apply machine learning methods and data mining algorithms. This is said by Rymarczuk [63], Javed et al. [64], Ahsan et al. [65], and Alshaibi et al. [66], who substantiate the need to develop algorithms to protect against cyber attacks using cyber machines that use various machine learning and deep learning methods, since mathematical models alone are not enough to deal with modern cybersecurity risks. In addition, the authors of [67] separately highlight the academic community, which, of course, is in the sphere of activity in which cybercrimes often occur, the degree of protection against which affects the significance of the level of national cybersecurity in each country. Another field of cyber attacks is the engineering of cyber-physical systems, which are controlled or monitored by machine algorithms and have software that is closely related to physical objects [68]. Therefore, it is advisable to use both a powerful mathematical apparatus and methods of fuzzy logic and machine learning to detect and prevent cyber threats [69]. It is also important to create common security policies [70]; conduct research on IoT cybersecurity [71], applications of the cybersecurity knowledge graph [72], and e-commerce cybersecurity [73,74]; and educate in the use of social media [75].

5. Conclusions

5.1. Implication

Thus, a study of the impact made by socio-economic transformation digitalization based on the developed quantile regressions analyzes how digital development for countries with high levels of digitalization and countries with low levels of digital development depends on national cybersecurity and ease of doing business. It also observes which groups of countries have the least resistance to risk factors for their involvement in fraudulent schemes for money laundering. The values of the variation coefficient confirm the high level of convergence between the studied countries in the degree of Internet use for electronic transactions in various directions. The average trend of the digital development dependence has been revealed using the econometric regression model.

5.2. Limits and Future Research Topic

Further research will be aimed at the development of multivariate adaptive regression spline (MARS) models to strengthen the financial cybersecurity of a country, as well as the creation of a road map for the development of an innovative system for countering the legalization of criminal proceeds and financial cyber protection.

In addition, taking into account the dependence on online technologies; the growth of misinformation caused by the pandemic, politics, and other social factors; the growth of cyber attacks; and the issue of digital trust and the interaction of factors that determine it is an urgent issue for further research. The analysis of canonical correlations between the digital environment and attitudes towards digital trust, between behavior in the digital space and the digital environment, between the behavior in the digital space and the digital experience of users, and between the digital environment and the digital experience of users is planned to be carried out using the tools of multidimensional statistics.

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Appendix A

Table A1. Fragment of initial data.

Country/Indicator	DDL	NCSI	TINY	SEES	Basel AML Index
1. Afghanistan	19.5	11.69	44.2	44.1	8.16
2. Albania	48.74	48.05	71	67.7	5.72
3. Argentina	60.41	48.05	70	59	6.50
4. Armenia	55.06	35.06	87.7	74.5	4.63
5. Australia	78.68	66.23	82.3	81.2	3.75
6. Austria	77.29	68.83	87.7	78.7	4.42
7. Azerbaijan	54.78	37.66	77.3	76.7	5.31
8. Bahrain	66.04	25.97	79.7	76	4.50
9. Bangladesh	33.11	67.53	34.9	45	5.84
10. Belgium	75.34	93.51	70.6	75	3.94
...	...	...	...	...	...
77. Poland	66.61	87.01	82.3	76.4	4.34
78. Portugal	68.25	89.61	83.3	76.5	3.85
79. Romania	60.67	71.43	53.7	73.3	4.76
80. Russian Federation	64.22	71.43	97.5	78.2	5.49
81. Saudi Arabia	63.46	83.12	91.8	71.6	5.12
82. Senegal	33.04	15.58	65.2	59.3	7.25
83. Serbia	59.85	77.92	73.2	75.7	5.47
84. Singapore	80.26	71.43	91.8	86.2	4.65
...	...	...	...	...	...
96. Ukraine	55.95	75.32	62.5	70.2	5.21
97. United Arab Emirates	68.01	40.26	100	80.9	5.91
98. United Kingdom	81.55	77.92	96.9	83.5	4.05
99. United States	81.44	79.22	82.2	84	4.60

Table A1. *Cont.*

Country/Indicator	DDL	NCSI	TINY	SEES	Basel AML Index
100. Uruguay	63.99	48.05	82.1	61.5	3.98
101. Uzbekistan	49	31.17	86.9	69.9	5.71
102. Vietnam	47.69	36.36	88.2	69.8	7.04
103. Zambia	29.66	55.84	62.1	66.9	6.03
104. Zimbabwe	28.97	15.58	48.6	54.5	6.79

Table A2. Standardized values of the observed indicators.

Country/Indicator	DDL	NCSI	TINY	SEES	Basel AML Index
1. Afghanistan	0.018	0.052	0.005	0.005	0.938
2. Albania	0.304	0.410	0.209	0.333	0.640
3. Argentina	0.607	0.410	0.186	0.085	0.778
4. Armenia	0.464	0.219	0.762	0.650	0.406
5. Australia	0.917	0.713	0.589	0.872	0.240
6. Austria	0.905	0.749	0.762	0.807	0,362
7. Azerbaijan	0.456	0.251	0.404	0.740	0.553
8. Bahrain	0.739	0.129	0.493	0.713	0.379
9. Bangladesh	0.075	0.731	0.001	0.006	0.663
10. Belgium	0.886	0.944	0.200	0.672	0.272
...	...	...	...	...	...
77. Poland	0.751	0.914	0.589	0.729	0.346
78. Portugal	0.782	0.927	0.624	0.732	0.257
79. Romania	0.613	0.781	0.020	0.596	0.434
80. Russian Federation	0.699	0.781	0.933	0.792	0.592
81. Saudi Arabia	0.682	0.890	0.855	0.515	0.512
82. Senegal	0.074	0.067	0.100	0.089	0.871
83. Serbia	0.592	0.849	0.269	0.701	0.588
84. Singapore	0.929	0.781	0.855	0.947	0.410
...	...	...	...	...	...
96. Ukraine	0.824	0.488	0.069	0.447	0.532
97. United Arab Emirates	0.287	0.778	0.953	0.865	0.677
98. United Kingdom	0.849	0.938	0.927	0.914	0.291
99. United States	0.860	0.937	0.585	0.921	0.400
100. Uruguay	0.410	0.694	0.581	0.130	0.279
101. Uzbekistan	0.176	0.310	0.740	0.433	0.638
102. Vietnam	0.235	0.281	0.775	0.428	0.849
103. Zambia	0.545	0.053	0.066	0.299	0.700
104. Zimbabwe	0.067	0.049	0.009	0.037	0.819

Appendix B

Table A3. Defining the target function to minimize total losses.

Country	DDL	Constant	NCSI	SEES	Forecast	Error	Loss
Afghanistan	0.018	1	0.052	0.005	0.008	0.010	0.005
Albania	0.304	1	0.410	0.333	0.364	−0.060	0.030
Argentina	0.607	1	0.410	0.085	0.188	0.418	0.209
Armenia	0.464	1	0.219	0.650	0.524	−0.060	0.030
Australia	0.917	1	0.713	0.872	0.851	0.066	0.033
Austria	0.905	1	0.749	0.807	0.818	0.087	0.044
Azerbaijan	0.456	1	0.251	0.740	0.599	−0.142	0.071
Bahrain	0.739	1	0.129	0.713	0.538	0.202	0.101
Bangladesh	0.075	1	0.731	0.006	0.243	−0.168	0.084
Belgium	0.886	1	0.944	0.672	0.789	0.097	0.048
...	...	...	...	...	...	...	...
Poland	0.751	1	0.914	0.729	0.819	−0.068	0.034
Portugal	0.782	1	0.927	0.732	0.826	−0.044	0.022
Romania	0.613	1	0.781	0.596	0.679	−0,066	0.033
Russian Federation	0.699	1	0.781	0.792	0.818	−0.119	0.059
Saudi Arabia	0.682	1	0.890	0.515	0.659	0.023	0.012
Senegal	0.074	1	0.067	0.089	0.073	0.001	0.000
Serbia	0.592	1	0.849	0.701	0.777	−0.185	0.092
Singapore	0.929	1	0.781	0.947	0.928	0.001	0.000
...	...	...	...	...	...	...	...
Ukraine	0.488	1	0.824	0.447	0.588	−0.100	0.050
United Arab Emirates	0.778	1	0.287	0.865	0.700	0.078	0.039
United Kingdom	0.938	1	0.849	0.914	0.928	0.010	0.005
United States	0.937	1	0.860	0.921	0.937	0.000	0.000
Uruguay	0.694	1	0.410	0.130	0.221	0.473	0.237
Uzbekistan	0.310	1	0.176	0.433	0.355	−0.044	0.022
Vietnam	0.281	1	0.235	0.428	0.372	−0.091	0.045
Zambia	0.053	1	0.545	0.299	0.387	−0.334	0.167
Zimbabwe	0.049	1	0.067	0.037	0.036	0.013	0.006

Source: calculated by the authors.

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