

Article

Connecting the Computer Skills with General Performance of Companies—An Eastern European Study

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Abstract: In the current era, the economic model that measures the dependence of the training offered by companies to their employees on certain variables allows for identifying the steps taken on account of digital transformations, given the fact that companies want to be competitive, to develop sustainably and the positive effect to it spreads globally. However, how digital transformation contributes remains unclear in both the literature and practice. Five descriptors of information on the economy in relation to the digital economy were extracted from the Eurostat database, and data on eight Eastern European countries in the period 2012–2020 served as primary data in the analysis. A generalized linear model was used as a statistical tool to infer the data series. Following the statistical regression analysis, it was found that the variable measuring the share of companies that offered training for the development/improvement of information and communication technology (ICT) skills is influenced by the combined effect of several other variables: ‘country’, ‘country × year’, ‘country × share of ICT personnel in total employees’, year × “share of ICT sector in GDP”. Based on the results, we noticed that the studied countries are included in two groups with distinct features, which influence the obtained GLZ model, showing the increase in the dependency effect or, on the contrary, the decrease in this effect.

Keywords: digital economy; digital transformation; sustainable development; dependency effect



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1. Introduction

Technological evolution has contributed to the emergence of the digital economy (DE) and global economic development. The extent of the global digital economy indicates a rapid growth trend, which, according to several authors, has produced consequential effects on operational performance [1–3], productivity [4,5] and innovation [6–8]. In the context of the DE, digital transformation (DT) is considered an essential strategic choice for enterprises to improve sustainable development [9], streamline production by optimizing resources and promote sustainable innovation [10].

Thus, from the original definition of the DE [11], we arrive at the DT that involves a combination of innovation, technology and data business model [12]. DT becomes a process that involves the remodeling of production and operating modes [13,14], but also a process based on the expansion of key technologies of the enterprise towards sustainable transformation [9,15]. At the enterprise level, as in life, we see Darwin’s principle of “survival of the fittest” at work, thus observing DT that involves innovative behavior that can fundamentally change products, business practices and the business environment [16,17]. In this context, the ability of enterprises to take advantage of the opportunity of DT, to capitalize on the advantages of digital technology and increase their competitiveness through sustainable development is a permanent concern of enterprise management [18].

The report on the DE 2024 emphasizes the need for inclusive and sustainable digitization strategies for developing countries that bear high costs (through the exploitation

of raw materials) and often reap few benefits [19]. In addition, we observe that in some countries with emerging economies, the development of enterprises is blocked by the lack of access to high-performance technology, which produces the decoupling of trade and difficulties in keeping up with technology [20,21], followed by the disruption of research and development (R&D) and supply, and sometimes even through market entry bans [22].

The specialized literature includes several debates regarding the development and innovation of enterprises in emerging economies (EEE) to promote innovation through mobility and the attraction of talents [23], but also the adoption of public policies of innovation networks in the country of origin [24]. Although EEE faces technical sanctions, product entry bans and supply chain disruptions [22,25,26], these challenges have contributed to adaptive organizational change by imposing new strategies of innovation and transformation of EEE based on extreme conditions [22,26]. This study aims to promote the digital transformation of enterprises in Eastern Europe by investigating the effect of digital transformation on economies and whether the influencing factors for different economies differ.

Analyzing the above problems, to capitalize on the DT for the development of the enterprise, the study identifies dependent variables that can influence the enterprises in the countries under study and provides the governments with a theoretical basis to formulate intervention policies to support the DT. Section 2 consists of the literature review, including existing studies on the DE and DT; DT in enterprises; the creation of information and communications technology (ICT) skills; and the nexus between DT, technology innovation and added value. Section 3 builds the theoretical framework to analyze the dependent variables and establishes the research methodology. Section 4 includes the results obtained after processing the material according to the research methodology. In Section 5, the conclusions regarding the obtained results are presented, and Section 6 presents the practical implications that define the research. Finally, Section 7 describes the limitations that the study encountered and presents possible future research.

2. Literature Review and Hypotheses Develop

2.1. Digital Economy and Digital Transformation

DE has also become important from the perspective of transformations produced at the enterprise level [12,27]. DT has modified the traditional business model, an aspect highlighted by the existing literature through numerous changes: in the organization of processes for value creation, in the use of digital technologies, in the creation of more dynamic production capacities, in consumer behavior and the strategic response of companies [28–30].

Through DT, enterprises gain market information, thus reducing information asymmetry and providing development opportunities for technology innovation [31–33]. In addition, DT also produces effects on the environment: reducing pollution emissions [7,34,35] and energy consumption [36,37], leading to energy efficiency [38]. The present study did not allow for measuring the DE and DT among the countries studied, but it considered that the DT exists to a greater or lesser extent in each country and thus focused on verifying the produced effect. Therefore, the proposed research hypothesis 1 (H1) is:

H1. *There is a dependency between the companies that provided ICT skills development training and the companies that received online orders.*

2.2. Digital Transformation in the Enterprise by Creating ICT Skills

Although digitization does not have a direct role in the production process, it leaves its mark on other factors in the production process, leading to increased efficiency [39]. Through the interaction between digitization and human capital [40], enterprises are transformed, and employees quickly acquire new knowledge and skills because of modern technologies [41].

The adoption of digital technology is faced with the need to have a qualified workforce and stakeholders who know the importance of digital technology and who, together with managers, are making efforts to support change and fast adoption [28,42,43].

In addition, their efforts must be supported by an appropriate adaptation of digital skills and tools with the vision for digitization/DT so that the potential offered is best exploited [44]. Focusing on the structural perspective of human capital vis-à-vis the need for improvement, Ma and Zhu analyzed the role of human capital and observed that DE provides a large and interested human capital for green technology innovation [45].

DT can improve the image of enterprises by integrating digital social platforms and thus facilitate the exchange of information with interested parties, helping them to decide on investment activity [46,47]; this openness and using new appropriate content that they need can lead to improved speed and efficiency of financing [48].

According to the information provided by the specialized literature regarding the need to adapt economies in order to become sustainable through digital transformation, which involves changes in the level of technologies and the skills of employees, we consider the analysis of the dependency relationship between companies that offered training for the development of skills and the volume of ICT personnel in total employment is important because it allows the identification of factors at the level of the countries under study. Therefore, we propose hypothesis 2 (H2) as follows:

H2. *There is a dependency between the companies that provide ICT skills development training and the volume of ICT staff in total employment.*

2.3. Nexus Between Digital Transformation, Technology Innovation and Added Value

According to the studies of Verhoef et al., DT and technological innovation found in business models have changed consumer behavior at the level of expectations and habits, created pressure on businesses through the urgent need to assimilate them, and determined changes at the level of the market [49]. Moreover, in recent years, the companies within the economies have also faced changes in exogenous factors (caused by the phenomena of economic cyclicity, climate change and armed conflicts), which have contributed to the DT of the companies [50]. Through DT and information technologies, companies and entrepreneurs achieve rapid information transfer, a better connection with suppliers and consumers through accessible information in real-time and thus can provide/receive responses to markets and supply chains, enabling the implementation of rapid changes that lead to the optimization of resource allocation and innovation [10,51].

The introduction of digital technology determines the emergence of new digital products and services that can later be developed, implicitly leading to the expansion of the company's customer base [52]. New technologies require DT at the enterprise level, which will facilitate the creation of better links between companies (it will allow a better allocation of production factors by reducing costs and improving operational efficiency [53], and it will lead to the innovation of products and processes (through increased productivity and lower costs) while having a lasting positive effect on the environment (through green technologies obtained through innovation and digital transformation) [54,55]. In addition, companies can use remote experts for assistance in various processes, which allows for better satisfaction of customer needs [56]. DT also produces effects in managerial work by improving business results at the organizational level, which leads to increased productivity [57,58] and, subsequently, incomes that will be reflected in GDP at the level of economies. Enterprises that adopt digital technology can create and maintain competitiveness through innovations that enable the creation, proposition, delivery and capture of value and improve energy efficiency, resulting in reduced environmental pollution [59,60]. Dou and Gao [61] and Wang et al. [62] showed that there is a positive relationship between DE and green technology innovation, especially in the context of heavily polluting industries, and Hao et al. [60] exemplifies how digital technology can contribute to the promotion of green innovation.

According to what was presented, the performance of companies is improved through the DT, which can be obtained through the introduction of digital technologies (these facilitating survival in volatile business environments through resilience and anti-fragility measures) and which causes companies to prosper by creating value [63]. Subsequently, the positive effect propagates both in companies and in the economies of countries, causing growth at the level of the gross domestic product and the value added. According to the above, we propose hypothesis 3 (H3) as follows:

H3. *There is a dependency between the companies that provided ICT skills development training and the share of the ICT sector in GDP/the share of the ICT sector in value added.*

By taking conceptual, empirical and contextual studies into account, we contributed to the existing studies by analyzing the economies of eight (ex-communist) countries to highlight differences between countries. Thus, by using five indicators that define the DE over a period of 9 years, we show the dependency relationship between the indicators for the Eastern European countries studied. The dependency relationships between the variables studied, which present information about the enterprises within the economies of the countries analyzed in the DT approach (emerging economies), have not been researched until now. The purpose of this study is to identify the influencing factors and the positive or negative addiction relationship they produce. To achieve this objective, three working hypotheses were formulated, and a GLZ model was highlighted, verified, and statistically validated. The influencing factors were analyzed using a statistical regression analysis from the specialized literature [61,64] to verify the dependence or association. This included Fischer's test and Student's *t*-test to measure goodness of fit and associated probability. Also, several distribution tests (Kolmogorov–Smirnov, Anderson–Darling and Chi-Squared) were performed for each variable to verify that the values of the variables are normally distributed and, therefore, the assumption of normality can be verified.

3. Materials and Methods

The study was carried out using statistical data published by the Eurostat database [65], which includes the results at the macroeconomic level obtained by the economies of some Eastern European countries during the years 2012–2020 (see Appendix A—Tables A1–A8). The processed information includes the changes produced in enterprises through the introduction of digital transformation and digital technologies as an effort to achieve the premise of adaptation and development of enterprises and sustainable economies.

Data on economic indicators include all sectors of activity except agriculture, forestry and fishing, mining and quarrying, and the financial sector.

The analysis considers the processing of the data obtained by each country because of the efforts to train company employees to develop skills in information and communication technology and in the use of the Internet, efforts aimed at supporting digital transformation, which will lead to sustainable economies. The eight countries included in this study are Bulgaria, Czech Republic, Estonia, Lithuania, Hungary, Poland, Romania, and Slovakia (see Table 1), and the information is according to the Eurostat methodology.

The countries studied are part of Eastern Europe, where the data can be compared from a geo-political point of view.

Digital transformation is recognized and necessary in enterprises as a means of obtaining, storing and exchanging knowledge, which determines and enables interaction with users, helping them to communicate freely and quickly with each other while ensuring the dissemination of learning throughout the organization. Digital transformation also plays an important role in enabling companies to achieve their goals by increasing sustainability awareness, which leads to changes in the means of production to provide greener goods and services [66–68]. On the other hand, changes in businesses and technological evolution leave their mark on the economies of each country, leading to the development of the digital

economy. Based on these considerations, several representative indicators were used to carry out this study, according to Table 2.

Table 1. The country list.

Label	Abbrev. Countries	Name of Countries
c1	BG	Bulgaria
c2	CZ	Czech Republic
c3	EE	Estonia
c4	LT	Lithuania
c5	HU	Hungary
c6	PL	Poland
c7	RO	Romania
c8	SK	Slovakia

c—country.

Table 2. The situation of the initial indicators, adapted from the Eurostat database.

No.	Abbrev.	Unit	Indicator Explanations
1	PEPT	%	Percentage of enterprises that provided training to develop/upgrade the ICT skills of their personnel
2	PICT	%	Percentage of the ICT personnel in total employment
3	PERO	%	Percentage of enterprises having received orders online (at least 1%)
4	PGDP	%	Percentage of the ICT sector * on GDP
5	PVAD	%	Percentage change in value added by the ICT sector at current prices

* The ICT sector included both the production (of components and electronic boards, computers and peripheral equipment, communication equipment, consumer electronics, and magnetic and optical media) as well as the part of services (telecommunications, computer programming, consulting and related activities, data processing, web hosting and portals, and repair of computers and communication equipment).

Using the information provided by the Eurostat database, we extracted the indicators from Table 2, which are part of the “digital economy and society” group; the respective subgroups are as follows: ICT use in enterprises (*PEPT* and *PERO*) and the ICT sector (*PVAD* and *PICT*) and *PGDP*). The indicators presented by the Eurostat database were obtained through the model’s annual questionnaire on the use of ICT (information and communication technologies) and e-commerce in the company. The strategy used in data collection is based on three pillars: (1) technology that works for people; (2) a fair and competitive digital economy; (3) an open, democratic and sustainable society [69].

The growth and stimulation of sustainable development, including the adoption of ICT, in accordance with Europe’s commitment to the 2030 Agenda for Sustainable Development, are measures monitored by the EU, and the impact can also be observed through the indicators studied (see SDG 8 and SDG 9) [70].

In the first part of the study, a preliminary analysis was carried out, which allowed the selection of indicators according to the intended purpose and the formulated hypotheses. The basis of this selection was, on the one hand, the availability of data provided by the Eurostat database and, on the other hand, the need to trace the dependence or independence between the variables. Knowing the information provided by the values recorded by the indicators studied for 8 years, at the level of 8 countries with emerging economies, allows us to see the progress made by each country thanks to the effort to create a “digital economy and society” with the effect of improving the competitiveness of the economy. Being an integral part of the way the company works, the use of ICT has left its mark on the way of managing production or service delivery processes, communication and management in general. The dependency relationship, if any, will allow us to signal the possibility of progress that economies can have due to the influence of some variables considered key.

The characteristics underlying the acquisition of information for the *PEPT* indicators include the following list: ICT systems and their use in enterprises; the use of the Internet and other electronic networks by enterprises; e-commerce and e-business processes; orga-

nizational aspects; ICT competence in the enterprise and the need for ICT skills; barriers to the use of ICT; the Internet and other electronic networks; e-commerce and e-business processes; security and trust in ICT; access to and use of the Internet and other information technologies network for connecting objects and devices (Internet of Things); access and use of technologies that provide the possibility to connect to the Internet or other networks from anywhere at any time (human-ubiquitous connectivity); the use of artificial intelligence; the use of cloud computing; the use of data analysis; the use of 3D printing; the use of robotics; the use of social networks; internet advertising; and ICT and the environment. The *PEPT* indicator, taken in the study, allows us to see the share of companies that have provided training for the development/modernization of their staff's ICT skills (including all companies with more than 10 employees). The *PEPT* indicator was chosen as a reference compared to the other indicators because we considered it important to observe whether the result obtained by it can be influenced by the size of the other indicators.

The *PERO* indicator includes the share of companies that received online orders (at least 1%). This indicator was chosen because we considered it useful and important to observe the way transactions are carried out at the country level, opposite the changes produced at the level of digital transformation companies.

The *PICT* indicator captures the characteristics of the labor force required to produce the wealth created by the ICT sector and the percentage of ICT personnel in total employment. This indicator is considered important in view of the differences that exist from one country to another and the need to capture possible relationships of interconditioning or dependence.

PGDP is expressed as the share of value added of the ICT sector in gross value added (approximation of GDP). The gross value added used in the calculation of the *PGDP* indicator is defined as production (at basic prices) minus intermediate consumption (at purchase prices), which is the balance of the production account of the national accounts. As it is a complex indicator that measures the effect obtained at the country level, it was chosen to capture the ways in which it can be influenced.

PVAD comprises the percentage change in value added by the ICT sector at current prices (the increase in value added by the ICT sector is defined at current prices between time t and time $(t - 1)$). The added value used to obtain the *PVAD* indicator, which is a composite indicator of net operating income, is important to study through the lens of dependence or independence, which can cause growth or decline in the economy at the country level.

Thus, to perform the analysis, we used the generalized linear model (GLZ), where the variables were separated by types and categories, according to Table 3.

Table 3. Status of variables in the analysis of the generalized linear regression model.

Name	Type	Sort
<i>PEPT</i>	Continuous	Dependent
<i>country</i>	Multinomial	Independent
<i>year</i>	Discrete	Independent
<i>PICT</i>	Continuous	Independent
<i>PERO</i>	Continuous	Independent
<i>PGDP</i>	Continuous	Independent
<i>PVAD</i>	Continuous	Independent

To design the model, the predictor variables (categorical: *country*; continuous: *year*, *PICT*, *PERO*, *PGDP* and *PVAD*) and the method (method: full factorial) used were selected. The study of the relationships between the indicators and the identification of the dependence factors is important at the macroeconomic level, and the choice of the *PEPT* variable as the dependent variable is also supported by the efforts at the European level, given by the “digital Europe program” which emphasizes “Advanced Digital Skills” [71].

“STATISTICA 8.0” software (StatSoft Inc., Tulsa, OK, USA) was used for regression and graphical analyses of the obtained data. To design the model, the predictor variables (categorical: country; continuous: *year*, *PICT*, *PERO*, *PGDP* and *PVAD*) and the method (method: full factorial) used were selected (see Table 3).

The statistical analysis was performed using the regression technique for the generalized linear model (GLZ). This technique was chosen because it is a flexible generalization of ordinary linear regression that allows the model to be linked to the response variable by a link function and allows the magnitude of the variance of each measurement to be a function of its predicted value. Thus, it allows response variables that have arbitrary distributions (rather than simple normal distributions) and an arbitrary function of the response variable (the link function) to vary linearly with the predictors (instead of assuming that the response itself must vary linearly). The statistical analysis of the model was carried out in the form of an analysis of variance (ANOVA) for the *PEPT* variable in relation to the other variables (*PICT*, *PERO*, *PGDP* and *PVAD*). This analysis included the Fisher F-test (overall significance of the model), its associated probability p (F), the correlation coefficient R and the coefficient of determination R^2 , which measures the goodness of fit of the regression model. The testing of the dependent variable *PEPT* with the independent variables, using the GLZ analysis, led to the obtaining of the model, which shows the variables whose influence is statistically significant and which can influence the increase or decrease in the percentage of enterprises that provided training to develop/update the ICT skills of their staff. Gradually, variables that did not achieve a $p < 0.05$ for a coefficient were excluded from the model until the model that was statistically validated was made.

The explanation of the model can be achieved through the size and strength of the effect on the *PEPT* indicator, for which the following descriptive statistics were calculated: *df* (degree of freedom), *SS* (total sum of squares), *MS* (sum of squares model), *F-value* (for the F test) and the *p*-value. *SS* represents the total variation in the data in relation to their means (large values show that the data are less variable in relation to their means). *MS* is the variation that can be explained by the independent variables included in the regression model (the higher the value of *MS* relative to *SS*, the better the model explains the variation in the data). According to the analysis of variance associated with estimated regression (ANOVA), the *F-value* (for the F-test) is the test statistic used to assess the overall significance of the regression model. The F test compared the variance explained by the model (*SS*) with the unspecified variance or the residual variance (*SS*—residual sum of squares), reporting them and adjusting for the number of parameters estimated in the model. The *p* value associated with the *F-value* must be less than the associated threshold (of 0.05) so that the null hypothesis—that all regression coefficients are zero—is rejected, and then the regression model is significant.

The analysis also includes the Student's *t* value for the estimated coefficients and the associated probabilities $p(t)$.

The generalized linear model (GLZ) was chosen, which is a way to make predictions from data sets; it is more complex and based on a series of different probability distributions to find the model “the better”. The model uses, among other techniques, Bayesian hypothesis testing to predict outcomes. The generalized linear model extends simple linear regression by allowing each outcome of the dependent variable (*y*) to come from a wide range of probability distributions (normal, binomial, Poisson, or Gamma). The generalized linear model is based on 3 elements: a probability distribution from the exponential family, a linear predictor $\eta = X\beta$ (it provides information about the independent variables of the model) and a link function that links the linear predictor to the expected value.

For each variable, several tests were performed, such as Kolmogorov–Smirnov, Anderson–Darling and Chi-Squared, to determine if the values associated with the variables (*PEPT*, *PICT*, *PERO*, *PGDP* and *PVAD*) are normally distributed and thus verified the hypothesis of normality.

4. Results and Discussion

Following the statistical analysis through stepwise regression, a stepwise regression summary was obtained for the *PEPT* variable (see Appendix A—Table A2) in which the dependence of this variable with the other variables taken into the study, but also with pairs of variables that were grouped for to observe their simultaneous effect.

From the analysis (see Appendix A—Table A2), the *PEPT* variable is dependent on the following variables: $country \times year$, $country \times PICT$, $year \times PGDP$, $country$. This tells us that the cumulative or simultaneous effect among the economies of the contributing factors (the variables mentioned above) can be increased by stimulating companies to provide training for the development/modernization of ICT skills of their staff. Moreover, the wealth offered by the ICT sector, measured by the *PICT* indicator (opposite the share of ICT personnel in total), can determine consequences at the level of the gross added value obtained at the country level (through the effect of the *PGDP* indicator). This dependence is verified by the value obtained at the coefficient $p < 0.05$, which shows that the model is statistically validated.

To observe whether there was a relationship between the country (dependent variable) and the *PEPT* variable (independent), the correlation coefficient (R) was calculated, as shown in Table 4.

Table 4. The effect of variables: a test of the SS whole model vs. SS residual *.

Variable	Multiple R R^2		Adj. R^2	SS	Model df	MS	SS	Residual df	MS	F	p
<i>PEPT</i>	0.9976	0.9951	0.9885	2046.13	22	93.0059	9.9882	16	0.6243	148.9848	0.0000

R: Pearson's correlation coefficient; SS: sum of squares; df: degrees of freedom; MS: mean of squares; F: F-value; p : p -value; * 4 significant digits provided.

Table 4 summarizes the results of the test of the sum of squares (SS) of the full model versus the sum of squares of the residual. The calculated F value for the regressions was 148.9848 for *PEPT*, greater than the minimum tabulated F (22/16) value of 1.375 required to reach a 95% confidence level, confirming that all models fit the experimental data well. ANOVA analysis of the quadratic regression model showed that the model was highly significant, as evidenced by the low p -value of the Fisher F -test (F , regression mean square/residual mean square = 148.9848, see Table 4). This proved that the equation model, as expressed in Equation (1), provides an adequate model to describe the response of the *PEPT* experiment to the influencing factors. The model was found to be adequate for prediction over the range of variables used.

Under the active development of high technologies, it is fundamental for employees to have ICT skills, which ensure greater productivity in their work and contribute to knowledge management. As shown in Table 4, the coefficient of determination R^2 of the quadratic regression model was determined to be 0.9951, which tells us that training to develop and improve staff ICT skills is an essential determinant. Since the R^2 value is closer to 1.00, we have that the model is more powerful and predicts the response better [72]. This implies that 99.51% of the variation for the *PEPT* value is explained by the independent variables, and this also means that only about 0.49% of the variation is not explained by the model. These measures indicated that the overall accuracy and fit of the polynomial model were good and that the analysis of response trends using the model was reasonable. The high value of the correlation coefficient, $R = 0.9976$, indicated a good agreement between the experimental and predicted values of *PEPT*. Adjusted R^2 ($Adj-R^2$) is also a measure of goodness of fit, as it is an estimator of the variation in the dependent variable explained based on the model by the variation in the independent variables. Here, the $Adj-R^2$ value (0.9885) was very close to the corresponding R^2 value. This higher R^2 coefficient ensured a satisfactory fit of the quadratic model to the experimental data. Thus, the values show us that the model was well chosen. The ICT skills, defined by the ability to use the technological tools of information and communications to clearly define informational

problems; access information efficiently; evaluate reliability and authority; and organize and synthesize information for practical, responsible and ethical use, contribute to the level of the enterprise and then at the level of savings, which is an increased factor of dependence.

The GLZ model, which verifies the dependence relationship between the studied variables, respectively, between the dependent variable *PEPT* and the rest of the independent variables, is presented in Equation (1):

$$PEPT = a_0 + a_1 \times country + a_2 \times country \times year + a_3 \times country \times PICT + a_4 \times year \times PGDP \quad (1)$$

According to the GLZ analysis (model in Equation (1)) and the data obtained by the partial least squares method (see Appendix A—Table A3), we notice that the value of the *PEPT* indicator depends on the ‘country’, the correlation between the ‘country × year’ to which it belongs, the ‘country × PICT’, and of the correlation between *year × PGDP*. Thus, it can be said from the analysis of Equation (1) that the plus sign related to each factor shows the positive influence that each factor produces on the *PEPT* variable.

The coefficient “ a_0 ” is intercepted, and its value obtained from the data is 15.47.

The coefficient “ a_1 ”, giving weight to “country”, is significant in the model; it has positive values in the countries LT (5825.29), PL (1272.46) and RO (871.71), which shows us a link of direct dependence and negative values in the countries BG (−7312.58), CZ (−33.95), EE (−923.68) and HU (−947.38), which shows us an opposed connection.

The coefficient “ a_2 ” associated with *country × year* is significant in the model; it has positive values in the countries BG (3.66), CZ (0.02), EE (0.46), and HU (0.48), which shows us a link of direct dependence and negative values in the countries LT (−2.92), PL (−0.64) and RO (−0.44), which shows us an opposed connection.

The coefficient “ a_3 ” associated with *country × PICT* is significant in the model; it has positive values in the countries CZ (0.94), LT (26.16), PL (11.10) and RO (2.42), which shows us a link of direct dependence and negative values in the countries BG (−32.19), EE (−2.53) and HU (−6.42), which shows us an opposed connection.

The coefficient “ a_4 ” associated with *year × PGDP* is significant in the model; it has the value zero.

Thus, for the Sigma-restricted parametrization analysis related to the dependent variable *PEPT* and the independent variables presented in the model, Table 5 was obtained.

Table 5. Univariate tests of significance. Sigma-restricted parameterization analysis. Effective hypothesis decomposition.

The Effect of <i>PEPT</i>	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>p</i> *
<i>intercept</i>	1	25.66	25.66	41.11	0.000009
<i>country</i>	2	20.84	10.42	16.69	0.000121
<i>country × year</i>	2	20.80	10.40	16.66	0.000123
<i>country × PICT</i>	7	20.92	2.99	4.79	0.004547
<i>year × PGDP</i>	1	11.75	11.75	18.82	0.000509
<i>Error</i>	16	9.99	0.62		
<i>Total</i>	38	2056.12			

* According to the *p*-values, all the coefficients are statistically significant; thus, the hypothesis that the independent variables contribute to a statistically significant model cannot be rejected.

According to Table 5, several 12 observations were made, with the number of degrees of freedom (*df*) presented for each variable. Analyzing the values obtained by “*SS*” shows that within the model, the largest total variation in the data in relation to their average is found in “*country × PICT*”, “*country*”, “*country × year*”, and “*year × PGDP*”, which suggests that the data are more variable relative to their mean. The high values recorded at “*MS*” by comparison with the values recorded at “*SS*” show us that the model better explains the data variation. The higher values (over 20) obtained at *SS* by the singular or simultaneous action of one or two variables (“*country*”, “*country × year*”, and “*country × PICT*”) show

us the produced effect, which is smaller in relation to the average. The lower value (11.75) obtained for SS, from the simultaneous action of the variables “ $year \times PGDP$ ”, shows us that it can vary more in relation to the average. This makes us understand that any modification of *PEPT* (among companies related to training to develop/upgrade their staff’s ICT skills) will have much greater consequences on the value-added share of the ICT sector in gross value added (measured by *PGDP*). Higher values of the *F* statistic indicate that the model fits the data better.

Analyzing Table 5, we noticed that the values obtained by the “*p*” coefficient for all variables are small ($p < 0.05$), so they are statistically significant, which tells us that the model is valid and thus, we have an answer to the first research question H1 (there is a dependency between the companies that provided ICT skills development training and the companies that received online orders).

The statistical analysis led to obtaining the Pareto diagram, which is presented in Figure 1.

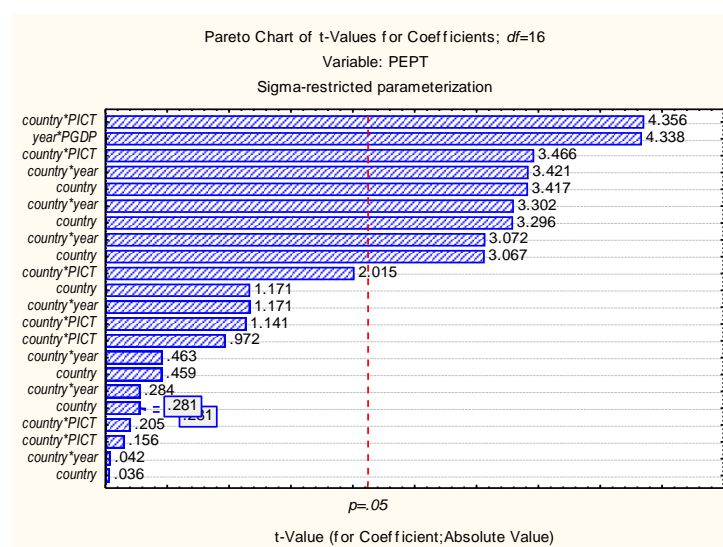


Figure 1. Pareto chart for *t*-values.

The Pareto chart in Figure 1 shows us the estimated effects, the interactions, and the standard deviation of each of the effects (measuring the sampling error). The Pareto chart, a frequency histogram in experimental design, shows us the amount of effect each factor has on the response in descending order, and the line running through the columns indicates how large an effect must be (i.e., the length of a column) to be statistically significant.

In Figure 1, the reference line for statistical significance on the Pareto chart associated with the *PEPT* variable compared to the other variables is drawn by the *t*-value, where the *t*-value is the $(1 - \alpha/2)$ quantile of a *t*-value distribution, with degrees of freedom equal to those of the error term. The calculation of the standardized effect depends on the degrees of freedom for the term, and in Figure 1, we have the value of 16 degrees of freedom (*df*). The interactive terms for *PEPT*-*t* and the other variables, which are considered significant (corresponding to values of $p < 0.05$, see Appendix A—Table A3), are interpreted as follows:

- *country* \times *PICT*—the term associated with the value of -4.356 , which shows us a relationship of the opposite direction between the contribution of BG companies in developing ICT skills and the share of ICT staff in total staff;
- *year* \times *GDP* (the value of 4.338 shows that at the country level, there is a positive relationship between the year and the share of the ICT sector in GDP);
- *country* \times *PICT*—the term associated with the value of 3.466, which shows us that at the level of the LT economy, there is a positive relationship between the contribution of LT companies in developing ICT skills and the share of ICT personnel in total personnel;

- $country \times year$ —the term associated with the value of 3.421, which shows us that there is a positive relationship because of the existence of a correlation between the economy of BG and the years studied, vis-a-vis the share of companies that trained for the development of ICT skills;
- $country$ —the term associated with the value of -3.417 corresponds to the correlation between BG and *PEPT* and tells us that there is an opposite relationship between the BG economy and the share of companies that trained for the development of ICT skills;
- $country \times year$ —the term associated with the value of 3.3022 corresponds to the data pair HU \times year compared to the share of companies that trained for the development of ICT skills and shows us a direct, positive connection;
- $country$ —the term associated with the value of -3.296 , which shows us the connection between HU and *PEPT* and tells us that there is an opposite relationship between the economy of HU and the share of enterprises that trained for the development of ICT skills;
- $country \times year$ —the term associated with the value of -3.072 , which shows us the connection between LT \times year and *PEPT* and shows us that the combination between country and year at the LT level determines a negative or opposite effect;
- $country$ —the term associated with the value of 3.067 corresponds to LT and shows us a direct and significant link between the enterprises in the country's economy and the share of those who have invested in the development of ICT training skills.

We can thus say that the interaction between $country \times PICT$, $country \times year$, and $PGDP \times year$ had a significant effect on *PEPT*. These results suggested that mean volume and turnover rate had a direct relationship with *PEPT* activity under this condition.

The result also indicated that *country*, *PICT* and *PGDP* could act as limiting factors on *PEPT*, and small variations in their values will considerably change either the growth rate, the formation rate or both. The significance of the effects can be seen through Student's *t*-test and *p*-value (see Appendix A—Table A3), where we see that the larger the magnitude of the *t*-test and the smaller the *p*-value, the more significant the corresponding effect.

The positive effect of country (LT), $country \times year$ (BG and HU), $country \times PICT$ (LT), and $year \times PGDP$ indicated a linear effect of *PEPT* growth, while the negative effect of $country$ (BG, HU), $country \times year$ (LT), and $country \times PICT$ (BG) showed a linear effect of decreasing *PEPT*.

To see if the data were normally distributed, following multiple test recipes from [73,74], three tests were used: Kolmogorov—Smirnov, Anderson—Darling and Chi-Squared. After using the test for all variables (*PEPT*, *PICT*, *PERO*, *PGDP* and *PVAD*), the assumption of normality was verified, resulting in all variables being normally distributed, with no transformation required ("Identity function", was used correctly in the response function model; see Appendix A—Tables A4–A8). Thus, a probability density function was created for each variable (*PEPT*, *PICT*, *PERO*, *PGDP* and *PVAD*) to define the probability, as the random variable, of falling into a distinct range of values, excluding the possibility of taking any value. The function thus explains, for each variable, the probability density function of the normal distribution and how the mean and deviation exist (see Appendix A—Figures A1–A5).

Scientific curiosity led to the comparison of the variables studied to identify the possible dependence between the share of enterprises that offer training for the development of ICT skills (*PEPT*) and other variables that are included in the Eurostat database as statistical information on the digital economy and society (*PICT*, *PERO*, *PGDP* and *PVAD*), for Eastern European countries. According to the review of previous studies, this is the first empirical study to test this issue in this context.

Yonghong et al. investigated the relationship between digital transformation and financial performance through descriptive, correlation and multi-layer linear regression analyses on a sample of listed manufacturing companies [75]. The study shows that there is a significant positive impact of digital transformation on the financial performance of manufacturing companies, which can be seen by a small variation at an early stage, but as digitization deepens, the impact increases (see net sales margin and the total return

on the company's assets). Our study recognizes the positive relationship between digital transformation and financial performance but also brings the need for training by studying the dependency relationship between companies that have provided training for the development of skills among employees. Thus, in our study, we see that the countries are divided into two groups, some of which are positively influenced when they increase the number of employees with ICT skills, others negatively, and the share of gross capital formation is also a dependent variable.

Bilan et al. modeled the dependence of the level of knowledge management on technologies for the global economic system [76]. They obtained the overall positive influence of ICT factors in shaping economic outcomes, the most influential factors being related to the expansion of hardware and Internet use by employees and the development of digital communication tools with stakeholders, such as websites. Using the method of correlation–regression analysis and data from EU countries, they estimated the relationship between seven selected factors in the formation of the Global Knowledge Index (GKI), establishing that there are significant links with six out of seven elements studied. The closest links found in the study concern the indicators “use of computers and the Internet by employees” and “companies with a website”. Although this study links the positive influence of ICT factors to economic results, it measures the level of knowledge management. Our study focused only on the identification of the dependence factors in the companies that offered training for the development of skills among employees and their effect on the economy of the countries studied.

The study by Li et al. was conducted as a descriptive statistical analysis of explanatory variables (earnings performance and operational performance) and the role of corporate governance and executive incentive mechanisms in emerging markets [77]. It shows us that the effectiveness of digital technology in improving governance depends on the user's technical knowledge and skills. The results of the study show that digital transformation has a positive impact on mitigating the agency's problems, as it improves the quality of information and improves internal control standards. In comparison with our study, their study performs a descriptive statistical analysis on other variables intended to measure the operational performance of the company as an effect of the digital transformation. Our study complements this study, which underlines the effectiveness of digital technology in improving governance and the dependence on the user's technical knowledge and skills through the dependence factors associated with training for the acquisition of ICT skills by the employer at the level of countries with emerging economies, and groups the countries into two distinct groups because of their similarities and differences.

5. Conclusions

Following the statistical regression analysis, a stepwise regression summary was obtained for the variable *PEPT* (share of enterprises that trained staff to acquire ICT skills) at the level of the economies of the countries studied. The result provided by the model shows us the dependence of the *PEPT* variable on certain factors and the connection with the most influential factors. Thus, the *PEPT* indicator is influenced by the singular effect given by the variable ‘country’ along with the combined effect of the variables: ‘country × year’, ‘country × PICT’, ‘year × PGDP’. By analyzing the coefficients (a_1 , a_2 and a_3) related to the terms of the model, it was observed that there are two different trends that determine the separation of the countries into two groups (group 1 consisting of the countries LT, PL and RO and group 2 consisting of the countries BG, CZ, EE and HU). Thus, the positive values of the a_1 coefficient suggest that for group 1, the companies in those countries play a direct role, are dependent and can obtain results due to the training of employees by employers. The negative values recorded at the coefficient a_1 suggest that for group 2, although the enterprises in the economy have a dependency relationship, the effect of training reduces the dependency. The values recorded by the a_2 coefficient for the “country × year” variable show us that the effect is the opposite of the a_1 coefficient. Thus, the combined effect of the two variables produces the inversion of the groups, with group

2 obtaining an effect of increasing training dependence and group 1 a decreasing effect. At coefficient a_3 for the “*country* \times *PICT*” variable, the countries are again divided into two groups; CZ was added to the first group, thus having positive values, but also for group 2 negative values (BG, EE and HU).

The GLZ model obtained was also supported by the ANOVA analysis, which showed that it is statistically significant, with only 1% of the total variance not being explained by the model. The GLZ model, which verifies the dependency relationship between the studied variables, shows us that Hypothesis 1, “There is a dependency between the companies that offered ICT skills development courses and the companies that received online orders”, was not verified in the countries studied. The *PERO* indicator by which the dependency could be recognized is not in the GLZ model equation; this tells us that the training at the employee level carried out by the companies did not produce significant effects of increasing the number of online transactions, with there being no direct link that could be identified.

When testing hypothesis 2, “There is a dependence between the companies that offered ICT skills development courses and the volume of ICT personnel in total employment”, we found that the GLZ model verified it. The GLZ model, which verifies the dependency relationship, shows us that the cumulative effect given by ‘*country* \times *PICT*’ supports the existence of a dependency link; this was found to be a positive direct link for countries such as CZ, LT, PL and RO (group 1) and one negative for countries such as BG, EE and HU (group 2).

Hypothesis 3, “There is a dependence between the companies that provided ICT skills development training and the share of the ICT sector in GDP/the share of the ICT sector in value added”, was partially verified, finding the existence of a dependent relationship between *PEPT* and *PGDP* and absence of a dependency link between *PEPT* and *PVAD*. Thus, we see from the equation of the GLZ model that the training offered by the employer is dependent on the added value of the ICT sector in total gross added value, producing direct benefits. The absence of the *PVAD* indicator from the GLZ model shows us that the added value in the ICT sector is not directly influenced by the employer’s training of employees; thus, it is an indicator that depends on other factors.

6. Practical Implications

The obtained results reflect the available resources and the capacities of enterprises in the field of ICT use and provide a generalized assessment at the macroeconomic level. Our analysis suggests that, at the current stage, the most influential directions for the involvement of ICT in business processes are the development of skills and training of the staff by the employer, which produces a positive dependency effect on the increase in the number of employees who have ICT skills and who leads and to increase the share of gross capital formation from the ICT sector in total gross capital formation.

Based on the results obtained in the empirical research, decision-makers and practitioners in companies can make decisions as follows: (1) governments can support and encourage companies to train employees in the field of ICT that will thus contribute to the digital economy for sustainable development through regulations and subsidies (2); owners or practitioners in companies can more easily understand the influencing factors, thus contributing to a positive long-term bottom line. The present paper is also useful for academic researchers to understand the differences between countries in the transformations produced on the transformation path to a digital economy and the factors influencing business and the economy, allowing the development of new research approaches.

7. Limitations of the Study and Future Research

There are certain limitations of the study, some of which may be further investigated in the future. The presented model only includes the situation of some Eastern European countries (countries considered to be emerging economies), but the study can be extended to other countries as well. Choosing such connections and modeling their impact is

complicated by the dynamic development of ICT itself. At the same time, further research on the use of ICT by enterprises is essential, as the potential and effectiveness of the use of ICT in business processes lead to the development of a knowledge-based economy. In addition, recent experience (COVID-19) demonstrates the need for rapid adaptation to new conditions used by ICT in business processes to weaken the negative impact of external threats on enterprises, thus stabilizing economic activity.

Also, this study analyses quantitative data without being able to associate possible qualitative differences related to the socio-economic or political changes that occurred after the fall of the former communist bloc. In this sense, new studies related to determinants and problems in ICT development at the enterprise level can be considered perspectives for further research.

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Appendix A

Table A1. Initial data.

No.	PEPT	Country	Year	PICT	PERO	PGDP	PVAD
1	17.13	BG	2012	2.02	4.2	4.53	−2.17
2	19.43	BG	2014	2.19	5.6	4.88	4.08
3	13.78	BG	2016	2.59	5.4	5.36	6.88
4	15.60	BG	2018	2.85	5.7	6.07	6.09
5	14.13	BG	2020	3.2	8.3	7.37	11.37
6	33.08	CZ	2012	2.79	24.7	4.35	0.06
7	33.13	CZ	2014	2.81	26.5	4.27	−1.55
8	32.73	CZ	2016	2.96	26.6	4.27	0.68
9	35.00	CZ	2018	3.13	24.3	4.56	4.62
10	34.73	CZ	2020	3.35	29.6	5.05	7.23
11	22.95	EE	2012	3.41	11.2	4.7	−6.73
12	24.95	EE	2014	3.58	12.3	4.83	4.98
13	24.75	EE	2016	3.69	15.7	4.9	3.25
14	24.98	EE	2018	4.3	16.1	5.39	5.14
15	27.70	EE	2020	4.95	16.9	6.83	15.21
16	16.85	LT	2012	1.98	15	2.49	−0.06
17	16.85	LT	2014	2.22	18.2	2.56	6.41
18	18.03	LT	2016	2.46	18.6	2.99	0.76

Table A1. Cont.

No.	PEPT	Country	Year	PICT	PERO	PGDP	PVAD
19	17.90	LT	2018	2.64	21.5	3.13	3.44
20	23.30	LT	2020	3.03	27.8	3.8	8.9
21	23.10	HU	2012	3.64	9.8	5.69	−3.64
22	25.50	HU	2014	3.41	10.3	5.58	−3.45
23	26.43	HU	2016	3.49	12.2	5.63	−1.57
24	26.58	HU	2018	3.6	12.6	5.95	−0.22
25	27.05	HU	2020	3.75	14	6	−1.98
26	21.63	PL	2012	1.84	9	3.16	−4.21
27	22.25	PL	2014	2	9.9	3.09	1.05
28	22.93	PL	2016	2.29	10.7	3.23	2.66
29	24.70	PL	2018	2.54	12.6	3.58	6.99
30	29.13	PL	2020	2.78	14.2	3.77	3.79
31	9.05	RO	2012	1.71	5	3.02	3.01
32	9.75	RO	2014	1.95	7.5	3.31	5.04
33	10.03	RO	2016	2.27	7.4	3.62	8.09
34	9.50	RO	2018	2.52	8.6	3.71	4.18
35	10.85	RO	2020	2.74	17.7	4.25	14.48
36	30.88	SK	2012	2.79	12.2	4.68	5.99
37	25.55	SK	2014	2.86	11.9	4.16	
38	27.55	SK	2016	3.04	12.2	4	−7.74
39	26.10	SK	2018	3.31	13.3	4.11	−4.24
40	26.33	SK	2020	3.48	17.5	4.66	8.41

Table A2. Summary of stepwise regression; variable: *PEPT*. Forward stepwise *p* to enter: 0.05; *p* to remove: 0.05.

The Effect of PEPT	Steps	df	F to Remove	p to Remove	F to Enter	p to Enter	Effect Status
<i>country</i> × <i>year</i>	7	7	4.76037	0.004671			In
<i>country</i> × <i>PICT</i>		7	4.78735	0.004547			In
<i>year</i> × <i>PGDP</i>		1	18.81613	0.000509			In
<i>country</i>		7	4.76938	0.004629			In
<i>year</i> × <i>PERO</i> × <i>PGDP</i>		1			0.58793	0.455119	Out
<i>PVAD</i>		1			0.33530	0.571148	Out
<i>PERO</i>		1			0.37940	0.547160	Out
<i>year</i>		1			0.40609	0.533565	Out
<i>year</i> × <i>PICT</i>		1			1.29962	0.272159	Out
<i>country</i> × <i>PERO</i>		7			0.97907	0.499435	Out
<i>year</i> × <i>PERO</i>		1			0.37865	0.547548	Out
<i>PICT</i> × <i>PERO</i>		1			0.80311	0.384323	Out
<i>country</i> × <i>PGDP</i>		7			0.36352	0.902065	Out
<i>PGDP</i>		1			0.15291	0.701267	Out
<i>PICT</i> × <i>PGDP</i>		1			1.07537	0.316164	Out
<i>PERO</i> × <i>PGDP</i>		1			0.58984	0.454402	Out
<i>Country</i> × <i>PVAD</i>		7			1.62571	0.243708	Out
<i>year</i> × <i>PVAD</i>		1			0.33518	0.571219	Out
<i>PICT</i> × <i>PVAD</i>		1			0.04592	0.833208	Out
<i>PERO</i> × <i>PVAD</i>		1			0.11465	0.739599	Out
<i>PGDP</i> × <i>PVAD</i>		1			0.08650	0.772701	Out
<i>country</i> × <i>year</i> × <i>PICT</i>		7			1.09295	0.439898	Out
<i>country</i> × <i>year</i> × <i>PERO</i>		7			0.98465	0.496354	Out
<i>country</i> × <i>PICT</i> × <i>PERO</i>		7			1.40548	0.310238	Out
<i>year</i> × <i>PICT</i> × <i>PERO</i>		1			0.79869	0.385599	Out

Table A2. Cont.

The Effect of PEPT	Steps	df	F to Remove	p to Remove	F to Enter	p to Enter	Effect Status
country × year × PGDP		7			0.36566	0.900801	Out
country × PICT × PGDP		7			0.59055	0.750059	Out
year × PICT × PGDP		1			1.05203	0.321297	Out
country × PERO × PGDP		7			0.69391	0.677870	Out
PICT		1			1.32044	0.268507	Out
PICT × PERO × PGDP		1			1.09002	0.313000	Out
country × year × PVAD		7			1.62215	0.244648	Out
country × PICT × PVAD		7			1.11767	0.427892	Out
year × PICT × PVAD		1			0.04588	0.833273	Out
country × PERO × PVAD		7			0.89655	0.546952	Out
year × PERO × PVAD		1			0.11465	0.739607	Out
PICT × PERO × PVAD		1			0.01288	0.911136	Out
country × PGDP × PVAD		7			1.03176	0.471019	Out
year × PGDP × PVAD		1			0.08627	0.773001	Out
PICT × PGDP × PVAD		1			0.01286	0.911229	Out
PERO × PGDP × PVAD		1			0.01919	0.891668	Out
country × year × PICT × PERO		7			1.41165	0.308122	Out
country × year × PICT × PGDP		7			0.59437	0.747363	Out
country × year × PERO × PGDP		7			0.69765	0.675302	Out
country × PICT × PERO × PGDP		7			0.94240	0.520099	Out
year × PICT × PERO × PGDP		1			1.08458	0.314170	Out
country × year × PICT × PVAD		7			1.11335	0.429966	Out
country × year × PERO × PVAD		7			0.89456	0.548143	Out
country × PICT × PERO × PVAD		7			0.63692	0.717447	Out
year × PICT × PERO × PVAD		1			0.01294	0.910952	Out
country × year × PGDP × PVAD		7			1.02866	0.472648	Out
country × PICT × PGDP × PVAD		7			0.72048	0.659734	Out
year × PICT × PGDP × PVAD		1			0.01293	0.910968	Out
country × PERO × PGDP × PVAD		7			0.63600	0.718092	Out
year × PERO × PGDP × PVAD		1			0.01922	0.891577	Out
PICT × PERO × PGDP × PVAD		1			0.01186	0.914736	Out
country × year × PICT × PERO × PGDP		7			0.94595	0.518067	Out
country × year × PICT × PERO × PVAD		7			0.63514	0.718690	Out
country × year × PICT × PGDP × PVAD		7			0.71834	0.661186	Out
country × year × PERO × PGDP × PVAD		7			0.63430	0.719282	Out
country × PICT × PERO × PGDP × PVAD		7			0.41934	0.867578	Out
year × PICT × PERO × PGDP × PVAD		1			0.01177	0.915029	Out
country × year × PICT × PERO × PGDP × PVAD		7			0.41806	0.868405	Out

Table A3. Parameter estimates: Sigma-restricted parameterization for *PEPT*.

The Effect of the PEPT	Level of Effect	Column	Param.	Value			Cnf. Lmt		Beta (ß)	Value		Cnf. Lmt	
				Std. Err	t	p	−95.00%	+95.00%		St. Err. ß	−95.00%	+95.00%	
Intercept		1	15.47	2.412	6.41152	0.000009 *	10.4	20.58					
country	BG	2	−7312.58	2140.101	−3.41693	0.003532 *	−11849.4	−2775.77	−483.112	141.3878	−782.841	−183.384	
country	CZ	3	−33.95	927.882	−0.03659	0.971261	−2001.0	1933.07	−2.243	61.3014	−132.196	127.710	
country	EE	4	−923.68	788.870	−1.17089	0.258787	−2596.0	748.65	−61.024	52.1174	−171.508	49.460	
country	LT	5	5825.29	1899.572	3.06663	0.007378 *	1798.4	9852.20	384.853	125.4970	118.811	650.895	
country	HU	6	−947.38	287.460	−3.29568	0.004561 *	−1556.8	−337.99	−62.589	18.9913	−102.849	−22.329	
country	PL	7	1272.46	2771.975	0.45905	0.652376	−4603.9	7148.79	84.067	183.1332	−304.158	472.291	
country	RO	8	871.71	3107.129	0.28055	0.782650	−5715.1	7458.53	57.590	205.2754	−377.574	492.755	
country × year		9	3.66	1.071	3.42124	0.003500 *	1.4	5.93	487.900	142.6090	185.583	790.218	
country × year		10	0.02	0.469	0.04242	0.966691	−1.0	1.01	2.649	62.4572	−129.754	135.053	
country × year		11	0.46	0.395	1.17063	0.258887	−0.4	1.30	61.605	52.6254	−49.956	173.166	
country × year		12	−2.92	0.951	−3.07240	0.007289 *	−4.9	−0.91	−389.362	126.7289	−658.016	−120.709	
country × year		13	0.48	0.146	3.30220	0.004498 *	0.2	0.79	64.007	19.3831	22.917	105.097	
country × year		14	−0.64	1.388	−0.46319	0.649465	−3.6	2.30	−85.643	184.8977	−477.609	306.322	
country × year		15	−0.44	1.554	−0.28405	0.780019	−3.7	2.85	−58.816	207.0640	−497.772	380.141	
country × PICT		16	−32.19	7.389	−4.35632	0.000490 *	−47.9	−16.53	−6.108	1.4021	−9.081	−3.136	
country × PICT		17	0.94	6.059	0.15568	0.878230	−11.9	13.79	0.192	1.2349	−2.426	2.810	
country × PICT		18	−2.53	2.220	−1.14065	0.270802	−7.2	2.17	−0.611	0.5358	−1.747	0.525	
country × PICT		19	26.16	7.548	3.46625	0.003182 *	10.2	42.16	4.866	1.4040	1.890	7.843	
country × PICT		20	−6.42	3.189	−2.01495	0.061032	−13.2	0.33	−1.441	0.7153	−2.958	0.075	
country × PICT		21	11.10	11.428	0.97170	0.345660	−13.1	35.33	2.003	2.0609	−2.366	6.371	
country × PICT		22	2.42	11.821	0.20488	0.840251	−22.6	27.48	0.433	2.1143	−4.049	4.915	
year × PGDP		23	0.00	0.000	4.33776	0.000509 *	0.0	0.00	0.327	0.0754	0.167	0.487	

* Statistically significant value.

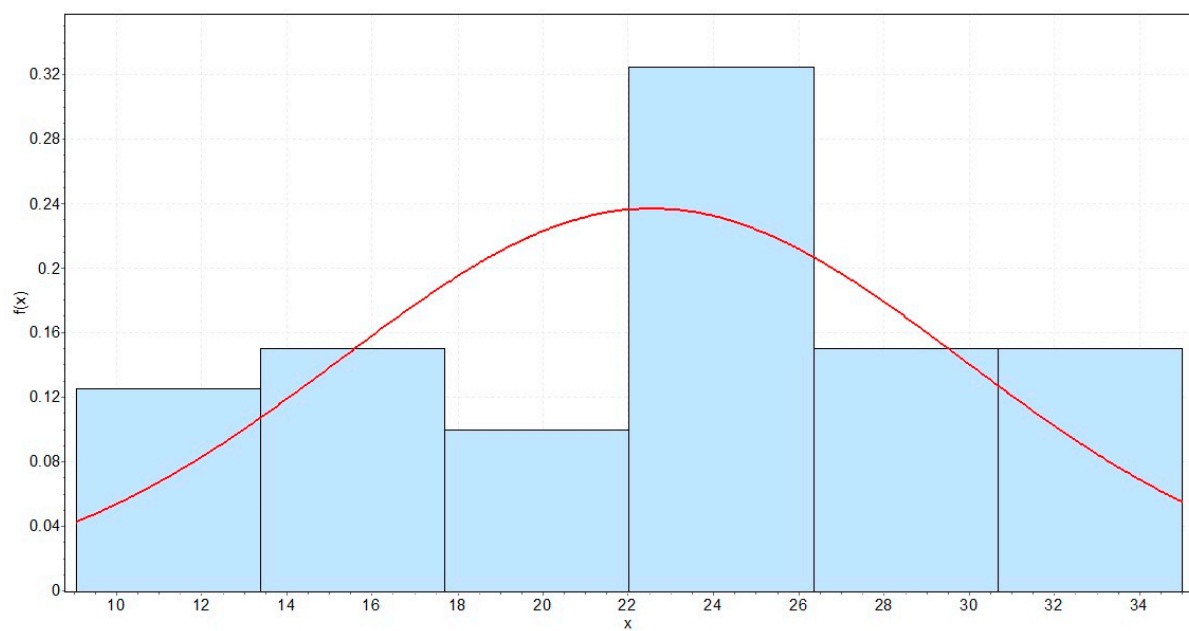


Figure A1. Probability density function for *PEPT*.

Table A4. The normality tests used for the *PEPT* variable.

Kolmogorov–Smirnov					
Sample Size	40				
Statistic	0.12082				
p-Value	0.56231				
Rank	2				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.16547	0.18913	0.21012	0.23494	0.25205
Reject?	No	No	No	No	No
Anderson–Darling					
Sample Size	40				
Statistic	0.55859				
p-Value	0.68798				
Rank	1				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	1.3749	1.9286	2.5018	3.2892	3.9074
Reject?	No	No	No	No	No
Chi-Squared					
Deg. of freedom	4				
Statistic	1.8945				
p-Value	0.75515				
Rank	2				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	5.9886	7.7794	9.4877	11.668	13.277
Reject?	No	No	No	No	No

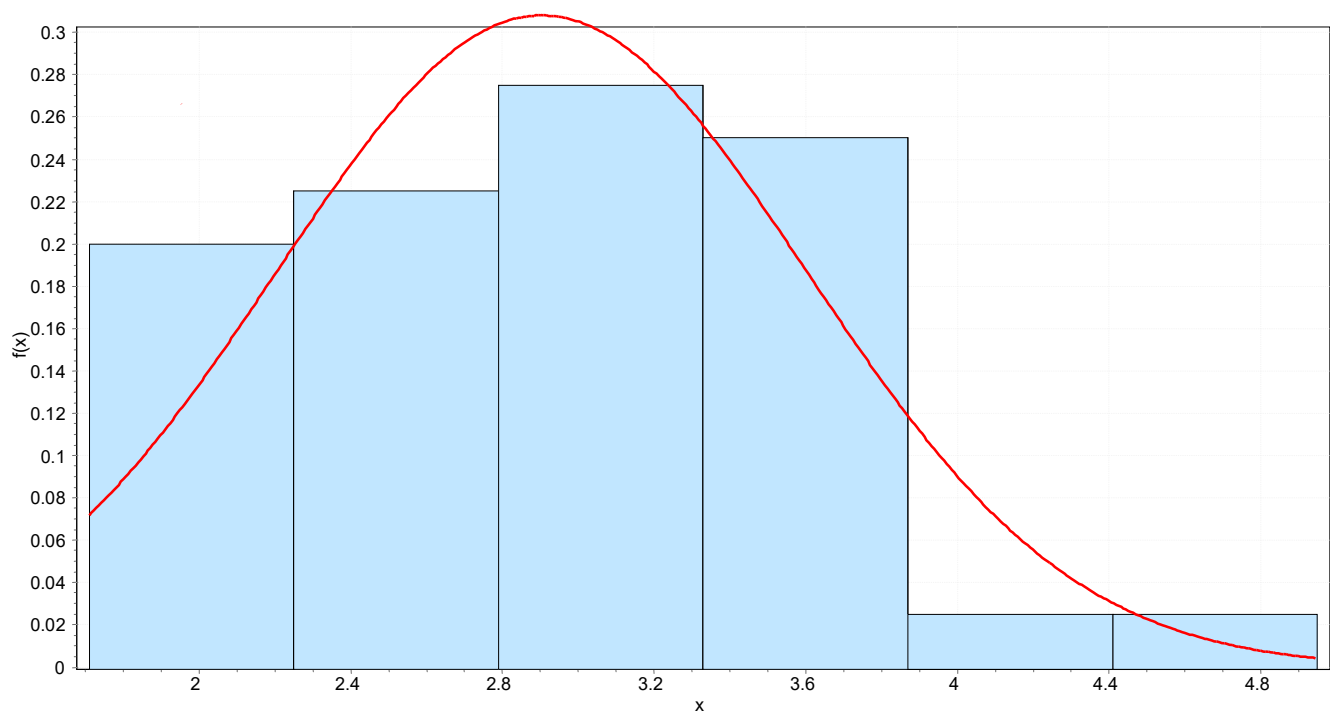


Figure A2. Probability density function for *PICT*.

Table A5. The normality tests used for the *PICT* variable.

Kolmogorov–Smirnov					
Sample Size	40				
Statistic	0.07508				
p-Value	0.96522				
Rank	1				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.16547	0.18913	0.21012	0.23494	0.25205
Reject?	No	No	No	No	No
Anderson–Darling					
Sample Size	40				
Statistic	0.27736				
p-Value	0.95540				
Rank	1				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	1.3749	1.9286	2.5018	3.2892	3.9074
Reject?	No	No	No	No	No
Chi-Squared					
Deg. of freedom	5				
Statistic	1.1759				
p-Value	0.94717				
Rank	2				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	7.2893	9.2364	11.07	13.388	15.086
Reject?	No	No	No	No	No

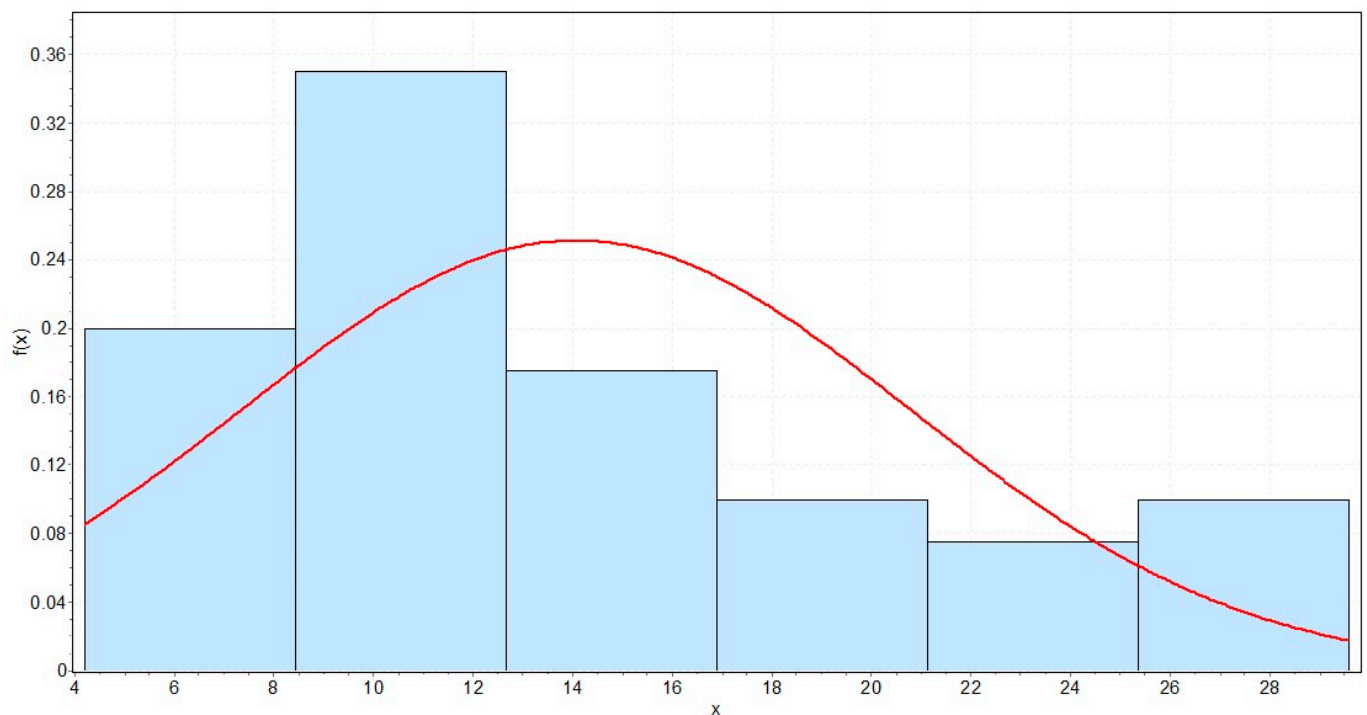


Figure A3. Probability density function for *PERO*.

Table A6. The normality tests used for the *PERO* variable.

Kolmogorov–Smirnov					
Sample Size	40				
Statistic	0.13665				
p-Value	0.40735				
Rank	2				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.16547	0.18913	0.21012	0.23494	0.25205
Reject?	No	No	No	No	No
Anderson–Darling					
Sample Size	40				
Statistic	0.8457				
p-Value	0.44903				
Rank	1				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	1.3749	1.9286	2.5018	3.2892	3.9074
Reject?	No	No	No	No	No
Chi-Squared					
Deg. of freedom	4				
Statistic	2.9813				
p-Value	0.56096				
Rank	1				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	5.9886	7.7794	9.4877	11.668	13.277
Reject?	No	No	No	No	No

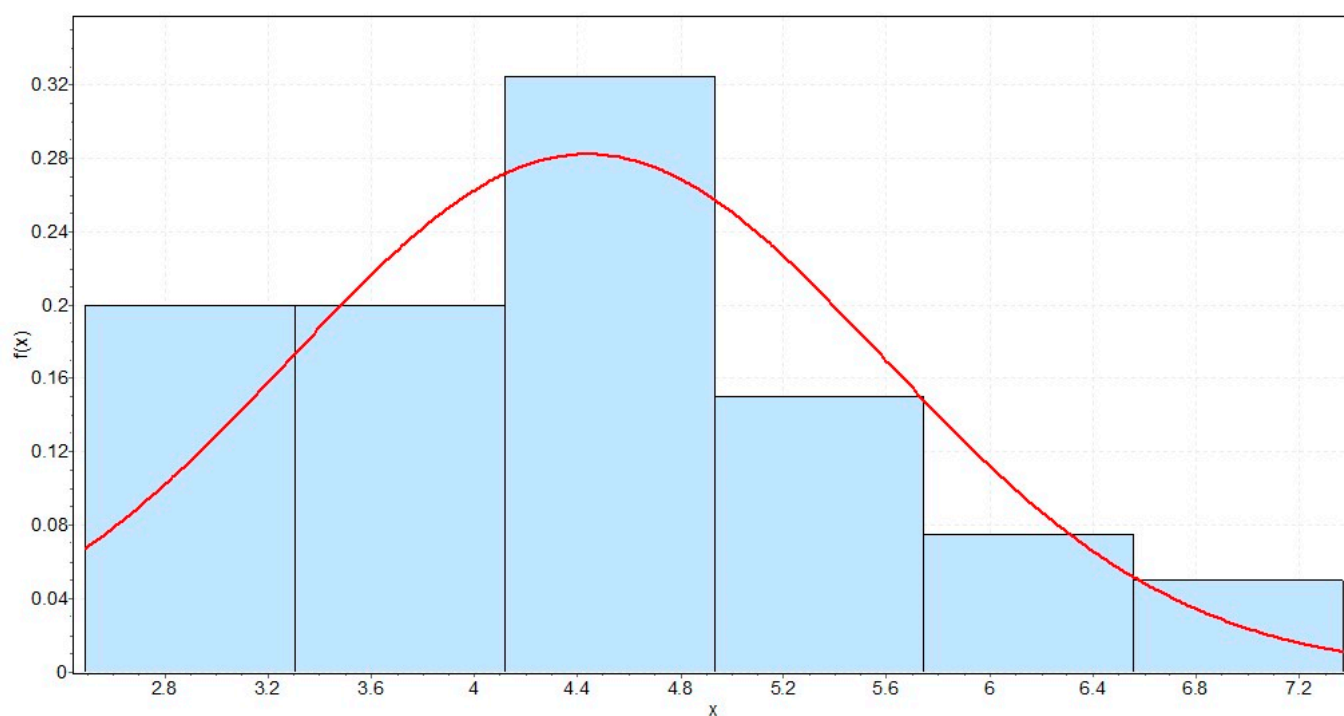


Figure A4. Probability density function for *PGDP*.

Table A7. The normality tests used for the *PGDP* variable.

Kolmogorov–Smirnov					
Sample Size	40				
Statistic	0.06888				
<i>p</i> -Value	0.98454				
Rank	1				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.16547	0.18913	0.21012	0.23494	0.25205
Reject?	No	No	No	No	No
Anderson–Darling					
Sample Size	40				
Statistic	0.25391				
<i>p</i> -Value	0.96945				
Rank	2				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	1.3749	1.9286	2.5018	3.2892	3.9074
Reject?	No	No	No	No	No
Chi-Squared					
Deg. of freedom	4				
Statistic	0.84117				
<i>p</i> -Value	0.93284				
Rank	2				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	5.9886	7.7794	9.4877	11.668	13.277
Reject?	No	No	No	No	No

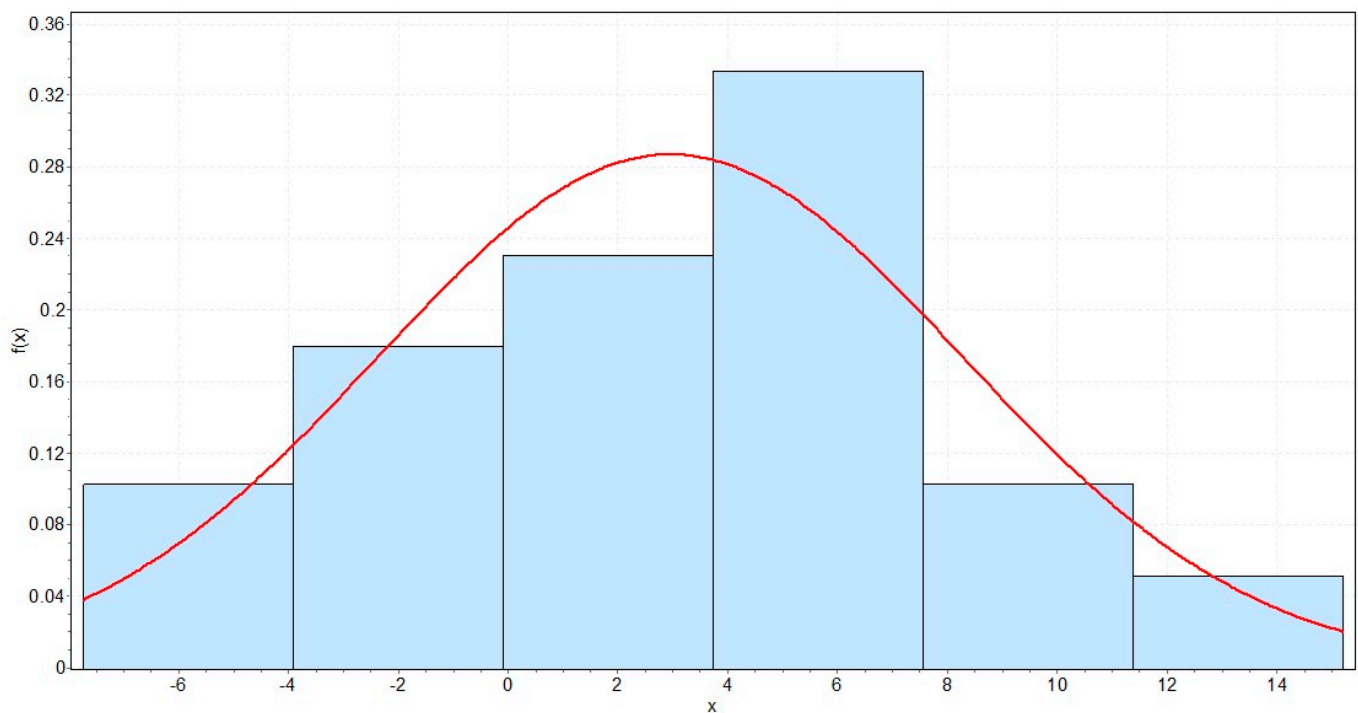


Figure A5. Probability density function for *PVAD*.

Table A8. The normality tests used for the *PVAD* variable.

Kolmogorov–Smirnov					
Sample Size	39				
Statistic	0.06826				
p-Value	0.98762				
Rank	2				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.16753	0.19148	0.21273	0.23786	0.25518
Reject?	No	No	No	No	No
Anderson–Darling					
Sample Size	39				
Statistic	0.21428				
p-Value	0.98686				
Rank	1				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	1.3749	1.9286	2.5018	3.2892	3.9074
Reject?	No	No	No	No	No
Chi-Squared					
Deg. of freedom	4				
Statistic	0.29413				
p-Value	0.99019				
Rank	1				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	5.9886	7.7794	9.4877	11.668	13.277
Reject?	No	No	No	No	No

References

1. Li, L.; Ye, F.; Zhan, Y.; Kumar, A.; Schiavone, F.; Li, Y. Unraveling the performance puzzle of digitalization: Evidence from manufacturing firms. *J. Bus. Res.* **2022**, *149*, 54–64. [\[CrossRef\]](#)
2. Zeng, H.; Ran, H.; Zhou, Q.; Jin, Y.; Cheng, X. The financial effect of firm digitalization: Evidence from China. *Technol. Forecast. Soc. Chang.* **2022**, *183*, 121951. [\[CrossRef\]](#)

3. Chen, W.; Srinivasan, S. Going digital: Implications for firm value and performance. *Rev. Account. Stud.* **2023**, *29*, 1619–1665. [CrossRef]
4. Guo, X.; Li, M.; Wang, Y.; Mardani, A. Does digital transformation improve the firm's performance? From the perspective of digitalization paradox and managerial myopia. *J. Bus. Res.* **2023**, *163*, 113868. [CrossRef]
5. Du, X.; Jiang, K. Promoting enterprise productivity: The role of digital transformation. *Borsa Istanbul. Rev.* **2022**, *22*, 1165–1181. [CrossRef]
6. Wen, H.; Zhong, Q.; Lee, C.C. Digitalization, competition strategy and corporate innovation: Evidence from Chinese manufacturing listed companies. *Int. Rev. Financ. Anal.* **2022**, *82*, 102166. [CrossRef]
7. Li, G.; Jin, Y.; Gao, X. Digital transformation and pollution emission of enterprises: Evidence from China's micro-enterprises. *Energy Rep.* **2023**, *9*, 552–567. [CrossRef]
8. Zhuo, C.; Chen, J. Can digital transformation overcome the enterprise innovation dilemma: Effect, mechanism and effective boundary. *Technol. Forecast. Soc. Chang.* **2023**, *190*, 122378. [CrossRef]
9. Bai, H.; Huang, L.; Wang, R. Supply chain financing, digital financial inclusion and enterprise innovation: Evidence from China. *Int. Rev. Financ. Anal.* **2023**, *91*, 103044. [CrossRef]
10. Wang, X.; Zhong, M. Can digital economy reduce carbon emission intensity? Empirical evidence from China's smart city pilot policies. *Environ. Sci. Pollut. Control Ser.* **2023**, *30*, 51749–51769. [CrossRef]
11. Shahbaz, M.; Wang, J.; Dong, K.; Zhao, J. The impact of digital economy on energy transition across the globe: The mediating role of government governance. *Renew. Sustain. Energy Rev.* **2022**, *166*, 112620. [CrossRef]
12. Peng, Y.; Tao, C. Can digital transformation promote enterprise performance? - from the perspective of public policy and innovation. *J. Innov. Knowl.* **2022**, *7*, 100198. [CrossRef]
13. Fernandez-Vidal, J.; Gonzalez, R.; Gasco, J.; Llopis, J. Digitalization and corporate transformation: The case of European oil & gas firms. *Technol. Forecast. Soc. Chang.* **2022**, *174*, 121293. [CrossRef]
14. Li, L. Digital transformation and sustainable performance: The moderating role of market turbulence. *Ind. Mark. Manag.* **2022**, *104*, 28–37. [CrossRef]
15. van Meeteren, M.; Trincado-Munoz, F.; Rubin, T.H.; Vorley, T. Rethinking the digital transformation in knowledge-intensive services: A technology space analysis. *Technol. Forecast. Soc. Chang.* **2022**, *179*, 121631. [CrossRef]
16. Bolboaca, S.D.; Jantschi, L.; Balan, M.C.; Diudea, M.V.; Sestras, R.E. State of Art in Genetic Algorithms for Agricultural Systems. *Not. Bot. Horti Agrobot.* **2010**, *38*, 51–63.
17. Liu, S.; Zhao, H.; Kong, G. Enterprise digital transformation, breadth of ownership and stock price volatility. *Int. Rev. Financ. Anal.* **2023**, *89*, 102713. [CrossRef]
18. Tian, X.; Lu, H. Digital infrastructure and cross-regional collaborative innovation in enterprises. *Financ. Res. Lett.* **2023**, *58*, 104635. [CrossRef]
19. UNCTAD. Digital Economy Report 2024: Shaping an Environmentally Sustainable and Inclusive Digital Future. Retrieved from United Nations. Available online: https://unctad.org/system/files/official-document/der2024_en.pdf (accessed on 15 July 2024).
20. Cui, V.; Vertinsky, I.; Wang, Y.; Zhou, D. Decoupling in international business: The 'new' vulnerability of globalization and MNEs' response strategies. *J. Int. Bus. Stud.* **2023**, *54*, 1562–1576. [CrossRef]
21. Khalid, U.; Ali, M.T.; Okafor, L.; Sanusi, O. Do sanctions affect the environment? the role of trade integration. *Res. Glob.* **2023**, *8*, 100191. [CrossRef]
22. Luo, Y. Illusions of techno-nationalism. *J. Int. Bus. Stud.* **2022**, *53*, 550–567. [CrossRef] [PubMed]
23. Verginer, L.; Riccaboni, M. Talent goes to global cities: The world network of scientists' mobility. *Res. Pol.* **2021**, *50*, 104127. [CrossRef] [PubMed]
24. Lee, C.; Yu, L. A multi-level perspective on 5G transition: The China case. *Technol. Forecast. Soc. Chang.* **2022**, *182*, 121812. [CrossRef]
25. Allen, J.S. Do targeted trade sanctions against Chinese technology companies affect US firms? evidence from an event study. *Bus. Polit.* **2021**, *23*, 330–343. [CrossRef]
26. Jacobs, B.W.; Singhal, V.R.; Zhan, X. Stock market reaction to global supply chain disruptions from the 2018 US government ban on ZTE. *J. Oper. Manag.* **2022**, *68*, 903–927. [CrossRef]
27. Taques, F.H.; Lopez, M.G.; Basso, L.F.; Areal, N. Indicators used to measure service innovation and manufacturing innovation. *J. Innov. Knowl.* **2021**, *6*, 11–26. [CrossRef]
28. Kraus, S.; Durst, S.; Ferreira, J.J.; Veiga, P.; Kailer, N.; Weinmann, A. Digital transformation in business and management research: An overview of the current status quo. *Int. J. Inf. Manag.* **2022**, *63*, 102466. [CrossRef]
29. Matarazzo, M.; Penco, L.; Profumo, G.; Quaglia, R. Digital transformation and customer value creation in Made in Italy SMEs: A dynamic capabilities perspective. *J. Bus. Res.* **2021**, *123*, 642–656. [CrossRef]
30. Müller, J.M.; Buliga, O.; Voigt, K.-I. The role of absorptive capacity and innovation strategy in the design of industry 4.0 business models—A comparison between SMEs and large enterprises. *Europ. Manag. J.* **2021**, *39*, 333–343. [CrossRef]
31. Song, M.; Xie, Q.; Shen, Z. Impact of green credit on high-efficiency utilization of energy in China considering environmental constraints. *Energy Pol.* **2021**, *153*, 112267. [CrossRef]

32. Song, M.; Peng, L.; Shang, Y.; Zhao, X. Green technology progress and total factor productivity of resource-based enterprises: A perspective of technical compensation of environmental regulation. *Technol. Forecast. Soc. Chang.* **2022**, *174*, 121276. [\[CrossRef\]](#)
33. Song, M.; Zheng, C.; Wang, J. The role of digital economy in China's sustainable development in a post-pandemic environment. *J. Enterp. Inf. Manag.* **2022**, *35*, 58–77. [\[CrossRef\]](#)
34. Shang, Y.; Raza, S.A.; Huo, Z.; Shahzad, U.; Zhao, X. Does enterprise digital transformation contribute to the carbon emission reduction? Micro-level evidence from China. *Int. Rev. Econ. Fin.* **2023**, *86*, 1–13. [\[CrossRef\]](#)
35. Wang, H.; Li, Y.; Lin, W.; Wei, W. How does digital technology promote carbon emission reduction? Empirical evidence based on e-commerce pilot city policy in China. *J. Environ. Manag.* **2023**, *325*, 116524. [\[CrossRef\]](#)
36. Xu, Q.; Zhong, M.; Li, X. How does digitalization affect energy? International evidence. *Energy Econ.* **2022**, *107*, 105879. [\[CrossRef\]](#)
37. Ma, Q.; Tariq, M.; Mahmood, H.; Khan, Z. The nexus between digital economy and carbon dioxide emissions in China: The moderating role of investments in research and development. *Technol. Soc.* **2022**, *68*, 101910. [\[CrossRef\]](#)
38. Lange, S.; Pohl, J.; Santarius, T. Digitalization and energy consumption. Does ICT reduce energy demand? *Ecol. Econ.* **2020**, *176*, 106760. [\[CrossRef\]](#)
39. Jones, C.I.; Tonetti, C. Nonrivalry and the Economics of data. *Am. Econ. Rev.* **2020**, *110*, 2819–2858. [\[CrossRef\]](#)
40. Litvinenko, V.S. Digital economy as a factor in the technological development of the mineral sector. *Nat. Resour. Res.* **2020**, *29*, 1521–1541. [\[CrossRef\]](#)
41. Du, J.; Song, M.; Xie, B. Eliminating energy poverty in Chinese households: A cognitive capability framework. *Renew. Energy* **2022**, *192*, 373–384. [\[CrossRef\]](#)
42. Proksch, D.; Rosin, A.F.; Stubner, S.; Pinkwart, A. The influence of a digital strategy on the digitalization of new ventures: The mediating effect of digital capabilities and a digital culture. *J. Small Bus. Manag.* **2021**, *62*, 1–29. [\[CrossRef\]](#)
43. Xie, X.; Han, Y.; Anderson, A.; Ribeiro-Navarrete, S. Digital platforms and SMEs' business model innovation: Exploring the mediating mechanisms of capability reconfiguration. *Int. J. Inf. Manag.* **2022**, *65*, 102513. [\[CrossRef\]](#)
44. Ko, A.; Feher, P.; Kovacs, T.; Mitev, A.; Szabo, Z. Influencing factors of digital transformation: Management or IT is the driving force? *Int. J. Innov. Sci.* **2022**, *14*, 1–20. [\[CrossRef\]](#)
45. Ma, D.; Zhu, Q. Innovation in emerging economies: Research on the digital economy driving high-quality green development. *J. Bus. Res.* **2022**, *145*, 801–813. [\[CrossRef\]](#)
46. Cao, S.; Nie, L.; Sun, H.; Sun, W.; Taghizadeh-Hesary, F. Digital finance, green technological innovation and energy-environmental performance: Evidence from China's regional economies. *J. Clean. Prod.* **2021**, *327*, 129458. [\[CrossRef\]](#)
47. Du, G.; Liu, Z.; Lu, H. Application of innovative risk early warning mode under big data technology in internet credit financial risk assessment. *J. Comput. Appl. Math.* **2021**, *386*, 113260. [\[CrossRef\]](#)
48. Zhou, X.; Du, J. Does environmental regulation induce improved financial development for green technological innovation in China? *J. Environ. Manag.* **2021**, *300*, 113685. [\[CrossRef\]](#)
49. Verhoef, P.C.; Broekhuizen, T.; Bart, Y.; Bhattacharya, A.; Qi Dong, J.; Fabian, N.; Haenlein, M. Digital transformation: A multidisciplinary reflection and research agenda. *J. Bus. Res.* **2021**, *122*, 889–901. [\[CrossRef\]](#)
50. Jesse, M.; Jannach, D. Digital nudging with recommender systems: Survey and future directions. *Comput. Hum. Behav. Rep.* **2021**, *3*, 100052. [\[CrossRef\]](#)
51. Kergroach, S. SMEs Going Digital: Policy Challenges and Recommendations. *Going Digital Toolkit Note* **2021**. Available online: https://goingdigital.oecd.org/data/notes/No15_ToolkitNote_DigitalSMEs.pdf (accessed on 20 July 2024).
52. Khin, S.; Ho, T.C. Digital technology, digital capability and organizational performance. *Int. J. Innov. Sci.* **2019**, *11*, 177–195. [\[CrossRef\]](#)
53. Gal, P.; Nicoletti, G.; Renault, T.; Sorbe, S.; Timiliotis, C. Digitalisation and productivity: In search of the holy grail—Firm-level empirical evidence from EU countries. *Int. Prod. Rep.* **2019**, *37*, 39–71. [\[CrossRef\]](#)
54. Zhu, F.; Li, Q.; Yang, S.; Balezentis, T. How ICT and R&D affect productivity? Firm level evidence for China. *Econ. Res.-Ekon. Istraz.* **2021**, *34*, 3468–3486. [\[CrossRef\]](#)
55. Luo, S.; Yimamu, N.; Li, Y.; Wu, H.; Irfan, M.; Hao, Y. Digitalization and sustainable development: How could digital economy development improve green innovation in China? *Bus. Strat. Environ.* **2023**, *32*, 1847–1871. [\[CrossRef\]](#)
56. Parise, S.; Guinan, P.J.; Kafka, R. Solving the crisis of immediacy: How digital technology can transform the customer experience. *Bus. Horiz.* **2016**, *59*, 411–420. [\[CrossRef\]](#)
57. Hai, N.T. Barreiras de transformação digital para pequenas e médias empresas no Vietna hoje. *Laplace Em Rev.* **2021**, *7*, 416–426. [\[CrossRef\]](#)
58. Chen, N.; Sun, D.; Chen, J. Digital transformation, labour share, and industrial heterogeneity. *J. Innov. Know.* **2022**, *7*, 100173. [\[CrossRef\]](#)
59. Teoh, M.F.; Ahmad, N.H.; Abdul-Halim, H.; Ramayah, T. Is Digital Business Model Innovation the Silver Bullet for SMEs Competitiveness in Digital Era? Evidence from a Developing Nation. *Vision* **2022**, 09722629221074771, OnlineFirst. [\[CrossRef\]](#)
60. Hao, X.; Li, Y.; Ren, S.; Wu, H.; Hao, Y. The role of digitalization on green economic growth: Does industrial structure optimization and green innovation matter? *J. Environ. Manag.* **2023**, *325*, 116504. [\[CrossRef\]](#)
61. Dou, J.; Gao, X. How does the digital transformation of corporates affect green technology innovation? An empirical study from the perspective of asymmetric effects and structural breakpoints. *J. Clean. Prod.* **2023**, *428*, 139245. [\[CrossRef\]](#)

62. Wang, C.; Yan, G.; Ou, J. Does digitization promote green innovation? Evidence from China. *Int. J. Environ. Res. Public Health* **2023**, *20*, 3893. [CrossRef] [PubMed]
63. Corvello, V.; Verteramo, S.; Nocella, I.; Ammirato, S. Thrive during a crisis: The role of digital technologies in fostering antifragility in small and medium-sized enterprises. *J. Amb. Intellig. Human. Comp.* **2023**, *14*, 14681–14693. [CrossRef] [PubMed]
64. Abideen, Z.U.; Fuling, H. Sustainability reporting and investor sentiment. A sustainable development approach to Chinese-listed firms. *J. Clean. Prod.* **2024**, *466*, 142880. [CrossRef]
65. Eurostat Database. Available online: <https://ec.europa.eu/eurostat/data/database> (accessed on 15 May 2024).
66. Chen, Y.; Wang, Y.; Zhao, C. From riches to digitalization: The role of AMC in overcoming challenges of digital transformation in resource-rich regions. *Technol. Forecast. Soc. Chang.* **2024**, *200*, 123153. [CrossRef]
67. Lu, H.T.; Li, X.; Yuen, K.F. Digital transformation as an enabler of sustainability innovation and performance—information processing and innovation ambidexterity perspectives. *Technol. Forecast. Soc. Chang.* **2023**, *196*, 122860. [CrossRef]
68. Mendez-Picazo, M.-T.; Galindo-Martin, M.-A.; Perez-Pujol, R.-S. Direct and indirect effects of digital transformation on sustainable development in pre- and post-pandemic periods. *Technol. Forecast. Soc. Chang.* **2024**, *200*, 123139. [CrossRef]
69. European Commission (EC). *Shaping Europe's Digital Future*; COM (2020); Publications Office of the European Union: Brussels, Belgium, 2020; Available online: https://commission.europa.eu/document/download/84c05739-547a-4b86-9564-76e834dc7a49_en?filename=communication-shaping-europes-digital-future-feb2020_en.pdf (accessed on 20 October 2024).
70. United Nations, Transforming Our World: The 2030 Agenda for Sustainable Development. Available online: <https://sdgs.un.org/sites/default/files/publications/21252030%20Agenda%20for%20Sustainable%20Development%20web.pdf> (accessed on 20 October 2024).
71. European Union. Regulation (EU) 2021/694 of the European Parliament and of the Council of 29 April 2021 Establishing the Digital Europe Programme and Repealing Decision (EU) 2015/2240. Available online: <http://data.europa.eu/eli/reg/2021/694/oj> (accessed on 20 October 2024).
72. Kaushik, R.; Saran, S.; Isar, J.; Saxena, R.K. Statistical optimization of medium components and growth conditions by response surface methodology to enhance lipase production by *Aspergillus carneus*. *J. Mol. Catal. B Enzym.* **2006**, *40*, 121–126. [CrossRef]
73. Jäntschi, L. A test detecting the outliers for continuous distributions based on the cumulative distribution function of the data being tested. *Symmetry* **2019**, *11*, 835. [CrossRef]
74. Jäntschi, L. Detecting extreme values with order statistics in samples from continuous distributions. *Mathematics* **2020**, *8*, 216. [CrossRef]
75. Yonghong, L.; Jie, S.; Ge, Z.; Ru, Z. The impact of enterprise digital transformation on financial performance—Evidence from Mainland China manufacturing firms. *Manag. Decision Econ.* **2023**, *44*, 2110–2124. [CrossRef]
76. Bilan, Y.; Oliinyk, O.; Mishchuk, H.; Skar, M. Impact of information and communications technology on the development and use of knowledge. *Technol. Forecast. Soc. Chang.* **2023**, *191*, 122519. [CrossRef]
77. Li, Z.; Xie, B.; Chen, X.; Fu, Q. Corporate digital transformation, governance shifts and executive pay-performance sensitivity. *Int. Rev. Finan. Anal.* **2024**, *92*, 103060. [CrossRef]

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